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MULTI-OBJECTIVE OPTIMAL CAPACITY AND PLACEMENT OF DISTRIBUTED GENERATORS IN THE POWER SYSTEM NETWORKS USING ATOM SEARCH OPTIMIZATION METHOD

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Declaration of Original Work

I, Ashwaq Faisal Alkhatib, the undersigned, a graduate student at the United Arab Emirates University (UAEU) and the author of this thesis entitled "*Multi-objective Optimal Capacity and Placement of Distributed Generators in Power System Networks Using Atom Search Optimisation Method*", hereby, solemnly declare that this thesis is my own original work that has been carried out and prepared under the supervision of Dr. Hussain Shareef in the College of Engineering at UAEU. This work has not been previously presented or published or formed the basis for the award of any academic degree, diploma or a similar title at this or any other universities. The materials derived from other sources (whether published or unpublished) and relied upon or included in my thesis have been properly cited and acknowledged according to appropriate academic conventions. Furthermore, I declare no potential conflict of interest with respect to the research, data collection, authorship, presentation and/ or publication of this thesis.

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Abstract

Nowadays, renewable energy sources become a significant source of energy in the new millennium. The continuous penetration of dispersed resources of the reactive power into power systems is predicted to introduce new challenges. Power loss mitigation and voltage profile development are the major investigation challenges that recently attracted the attention of researchers in the field of power systems. Distributed generation (DG) is widely preferred because it is a highly effective solution that strengthens the performance of power system networks. This multi-objective function study aims to minimise power losses in the feeders, sustain voltage levels and reduce the application cost of DGs by adapting the atom search optimisation simulated on MATLAB software. Two different IEEE power test systems, namely, a 33 bus radial distribution system (RDS) and a 14-bus power system that hosts 1, 2 and 3 DGs in both systems, are demonstrated in this research. Correspondingly, backward–forward sweep and Newton–Raphson power flow methods are used for each system. The proposed technique is compared with genetic algorithm particle swarm optimisation (GA-PSO) method. Results depict the effectiveness of the proposed method in minimising system power losses and in regulating the voltage profile where the power loss reduction is 25.38% in the 33 bus RDS using 2 DGs. By contrast, the power loss reduction percentages in the 14 bus system are 0.316% and 0.169% in systems with 1 and 2 DGs, respectively. The voltage profile has been enhanced compared with those in the original case and the results obtained from the GA-PSO method.

Keywords: Distributed Generation, Voltage Profile, Power Losses, Atom Search Optimisation, Multi-objective function.

Title and Abstract (in Arabic)

تحديد سعة وموقع مولدات الطاقة الموزعة في شبكات النظم الكهربائية باستخدام خوارزمية استكشاف الذرة

الملخص

في الآونة الأخيرة، أصبح استنزاف الموارد البشرية مؤشراً على ضرورة وحتمية استخدام مصادر الطاقة المتجددة، مما أدى إلى ظهور مشكلات عديدة في أنظمة وشبكات الطاقة الكهربائية ومن هذه المشكلات فقدان الطاقة الكهربائية على شكل حرارة في الأسلاك الكهربائية وحصول تذبذب في جهد المحطات الفرعية مما ينتج عنه خسائر مادية كبيرة. تعد مولدات الطاقة المتجددة من أحدث الوسائل المستخدمة حديثا للتغلب على هذه المشكلات، فقد أثبتت فاعليتها وكفاءتها في أنظمة الطاقة الكهربائية وشبكات التوصيل الكهربائي.

إن الأهداف الرئيسية لهذه الدراسة هي استخدام مولدات الطاقة المتجددة من أجل تقليل الخسائر الكهربائية في شبكات التوصيل الكهربائية والعمل على تنظيم الجهد في المحطات الفرعية وبالتالي تقليل الخسائر المادية لأنظمة الطاقة الكهربائية وذلك عن طريق استخدام خوارزمية بحث الذرة. وقد تم تطبيق هذه الخوارزمية عن طريق تطبيق حاسوبي يسمى الماتلاب. ولقد تمت عملية اختبار هذه الخوارزمية على نظامين معتمدين من معهد مهندسي الكهرباء والإلكترونيات (IEEE) وهما شبكة ال 33 محطة فرعية لخطوط التوزيع الكهربائية والنظام الآخر هو شبكة 14 محطة فرعية لشبكة الطاقة الكهربائية وذلك بإضافة وحدة طاقة متجددة واحدة في المرحلة الاولى ووحدتان في المرحلة الثانية وثلاث وحدات في المرحلة الأخيرة لكلا النظامين. من أجل الحصول على حسابات التدفق الكهربائية، استخدمت كل من طريقة المسح للخلف والامام وطريقة نيوتن رافسون. وللتأكد من النتائج التي ظهرت باستخدام هذه الخوارزمية، تمت المقارنة مع خوارزمية أخرى وهي خوارزمية الجينات - تجمع الجسيمات. وقد أثبتت النتائج مدى فاعلية هذه الخوارزمية المقترحة حيث تم تخفيض فقدان الطاقة الكهربائية في النظم الكهربائية بكفاءة وبفاعلية، وتم تحسين مستوى الجهد في المحطات الفرعية وبالتالي تم تقليل الخسائر المادية للنظم الكهربائية مقارنة مع الخوارزميات الأخرى.

مفاهيم البحث الرئيسية: مولدات الطاقة الموزعة، ملف تعريف الجهد، خسائر في القدرة، خوارزمية بحث الذرة، وظيفة متعددة الأهداف.

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Dedication

To my beloved parents, family and friends

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List of Abbreviations

ALO	Ant Lion Optimization
APL	Active Power Losses
ASO	Atom Search Optimisation
AVR	Automatic Voltage Regulation
CHP	Combined Heat And Power
CPU	Computer Processing Unit
DG	Distributed Generation
GA	Genetic Algorithm
GA-PSO	Genetic Algorithm-Particle Swarm Optimisation
KVA	Kilo Volt Ampere
KVAR	Kilo Volt-Amp Reactance
KW	Kilo Watt
MD	Molecular Dynamics
MINLP	Mixed Integer Nonlinear Programming
MVA	Mega Volt Amp
NR	Newton–Raphson
OCVC	Optimal Coordinated Voltage Control
OLTC	On-Load Tap Changer
PF	Power Factor
PQ	Active Power/ Reactive Power
PSO	Particle Swarm Optimisation
PV	Photovoltaic

RAC	Reduction Of Application Cost
RDS	Radial Distribution System
SCBs	Shunt Capacitor Banks
TCT	Tap Changing Transformers
VAR	Volt-Amp Reactance
VPI	Voltage Profile Improvement

Chapter 1: Introduction and Literature Overview

1.1 Introduction

Worldwide demand for electric energy is increasing because of the growth of the population and the economy. Electrical power energy plays an essential role in the inhabitants' life. Most equipment used in our life needs to use electrical power to operate. Rapid inventions and new technologies that are based on power energy are also expanding widely. Industrial evolution and social growth increased the demand for electrical energy. The electrical power system should be dependable, attainable, affordable and clean.

The electrical power system Figure (1) is divided into three main sections, namely, generation with high voltage, transmission with high medium voltage and distribution with medium low voltage. A distribution system that is closely attached to the clients is considered a significant part of the entire system. The voltage in the distribution system is stepped down for the user's utilisation. The system reliability is based on the efficiency of the distribution system. Given the rapid increase in the power demand and network extension, engineers must maintain the stability and reliability of the power system (Ghadi et al., 2019). The voltage magnitude is decreased when heavy burdens are attached to the power system, thereby increasing the power system losses. In the last decade, electrical bulk experienced many challenges in the power system because of the new lifestyle. A study reported that the distribution system has experienced 70% of the power losses because the ratio X/R in the distribution system is lower compared with the transmission system. This phenomenon leads to increased power loss and voltage violation, high total expenses and unreliable power system. Consequently, several methods, such as shunt capacitor banks (SCB), reconfiguration and on-location power generation, have been proposed to overcome these issues. Distributed generator (DG) in smart distribution systems is considered a new power generation technology. DG is a small-scale power generation that can be placed on-site directly to the distribution system as a grid-connected mode or connected to the customer as a stand-alone mode (Senjyu et al., 2018). The integration of DG in the distribution network can reduce power losses and enhance the voltage profile. The consumption trend of DG in the smart grid has been increasing rapidly because of fossil fuel depletion. DGs are effective in developing reliability, reducing power losses, improving the quality of the power system, minimising the investment cost and decreasing the greenhouse gas emissions (Vita, 2017). Many significant aspects, such as DG technology, number, size, type and location, must be considered in the implementation of DG.

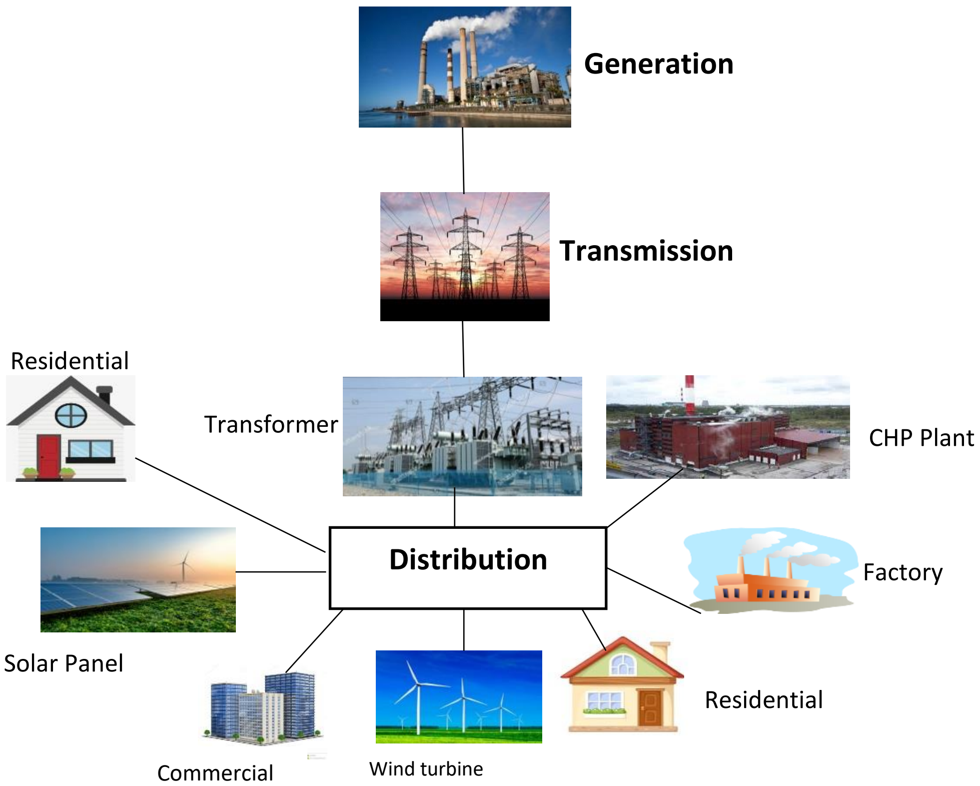

Figure 1: Electric Power Systems

The DGs can be classified as follows:

- Type 1: Only real power injection and operates at power factor (PF) = 1 (e.g. micro turbine, PV cells and fuel cells)
- Type 2: Only reactive power injection (e.g. capacitor banks, synchronous compensator and KVAR compensator)
- Type 3: Real and reactive power injections (e.g. cogeneration, synchronous machines and gas turbine)
- Type 4: Real power injection but reactive power consumption (induction generator in the wind farm)

Optimisation is a numerical tool used for investigating the optimal solution of the objective function where it can be minimised or maximised with specified conditions. The system aims to minimise the objective functions without breaking the constraints. A French scholar presented the optimal power flow in 1962. Decades have been spent to make the algorithm effective in resolving optimisation issues, which can be linear or complex (nonlinear) problems. Several techniques have been presented to resolve the optimisation challenges categorised as conventional or intelligent approaches. Such techniques include gradient technique, Newton method, quadratic programming, interior point method and linear programming. These techniques are distinguished for their rapid calculation and online computation. Furthermore, these techniques are inappropriate for some other problems that involve discrete variables because of their difficulty in approaching convergence and reaching global optima. In the previous decade, several modernised intelligent methods have been improved to cope with the complicated optimal power flow (OPF) issues, such as particle swarm optimisation (PSO), genetic algorithm (GA), ant–lion optimisation (ALO) and atom search optimisation (ASO). Meta-heuristic search optimisation, such as GA, was evaluated as an appropriate method for solving concurrent multidimensional issues for global optimal resolution. Moreover, GA can approach convergence smoothly and has complicated encoding and decoding processes (Devabalaj and Ravi, 2018). PSO is a meta-heuristic technique founded on the behaviour of flacks of birds and fish; this approach has better superior convergence than GA because of its integration of social mentality fundamental and preferable computation to improve the swarms' behaviour (Sadiq et al., 2019). Weiguo Zhao presented a recent meta-heuristic ASO in 2019. This algorithm is founded by mimicking the physical motion of atoms, as illustrated in the molecular dynamic (MD) simulation with less parameters to regulate (Zhao et al., 2019).

The DG size and location are considered complex nonlinear optimisation problems that request for multi-objective optimisation methods, such as reducing power losses, bus voltage fluctuation, carbon emission and short circuit capacity. Accordingly, the power network reliability is maximized. This thesis aims to specify the placement and capacity of DGs in the radial distribution system (RDS) and power systems. The real power loss and voltage profile at the nodes and the operating cost are considered the regulating parameters. The location and size of the DGs are determined by using the ASO technique.

1.2 Statement of the Problem

The integration of DGs in distribution systems has introduced several challenges and disadvantages in terms of the delivery of power quality, protection issues and voltage support. The need for distribution generators to control the voltage at its acceptable limits is required to maintain the power delivery to the customers.

Consequently, the power quality and loss issues are mitigated. Sizing and allocating the DGs in the power network issue has attracted power researchers to investigate in this field; the inappropriate placement and capacity of the DGS lead to power loss increment, voltage fluctuation, failure in protecting the power system, unstable system, harmonics and overall wastage in DG investment cost (Sadiq et al., 2019). Placing and sizing the DGs is not a straightforward issue but a complex power struggle that needs to be addressed cautiously.

1.3 Objective of the Work

This research aims to overcome the power losses associated with the misplacement of DGs and inaccurate sizing in RDSs and power network systems. The proposed system's goals are mainly power loss reduction, voltage profile enhancement and overall expense reduction for the power system. These goals will be attained as follows:

1- To investigate the effectiveness of the DGs in the power networks and the characteristics of DG technologies and by identifying the advantages and disadvantages of DGs to the power systems in radial distribution and transmission network systems.

2- To obtain the optimal location and capacity of the DGs in the power systems through the application of ASO algorithm and GA-PSO for comparison purposes.

3- To discuss the effectiveness of the ASO algorithm in resolving the issue of optimal location and capacity of DG in addition to presenting the remarkable influence of DGs in minimizing the power losses, voltage profile regulation and total cost reduction.

1.4 Literature Overview

1.4.1 Introduction

Nowadays, the massive demand for energy resources has been increased exponentially because of the rapid growth of the population. This situation is expected to introduce several challenges, such as voltage control and power losses as I^2R in the distribution level, in the electrical operational process. The electrical power network consists of a power station that transmits the energy to the end users via transmission and distribution feeders. Voltage stability is considered an essential aspect in power systems to satisfy the operational procedure for all the appliances, such as motors, bulbs and other loads in the market. Excessive voltage fluctuation caused by load variations leads to undesirable performance or even in the malfunctioning of the electrical devices. The power system can deal with the deviation in the voltage in a short time. Nevertheless, the system should be urgently brought back to the desirable limit to avoid the motor and generator from spoiling because of the increase in heating, decrease in transmission line losses and prevent the system from voltage collapse. According to C57-2017- IEEE/IEC International Standard, the acceptable limits of the variation in the voltage profile are specified to be approximately ±5% of the declared voltages at the busses (Bidgoli and Cutsem, 2018). The variation in the voltage at the customer’s properties is due to the alternation in the load on the power system. When the burden in the power system is increased, the voltage values at the end user substation would decrease because of the rapid failure in the voltage in the (a) alternator synchronous impedance, (b) transmission feeders, (c) transformer impedance and (d) distribution. Thus, specific techniques should be used to control the voltage in the power system in its acceptable limits. The strategies for controlling the voltage in the power system are presented in the following subsections.

1.4.1.1 Reactive Power Resources

Reactive power and voltage control are involved in the distribution systems to acquire the preferable voltage profile and reactive power flow. Certain equipment, such as capacitor banks, tap changing transformers (TCT) (Penkey et al., 2017) and DGs, has been used recently. Numerous researchers presented generator excitations, automatic voltage regulation and static VAR compensator methods to maintain the voltage levels within the specified limits, improve the reactive power performance, sustain the system stability and gain the ultimate benefits of the power network (Aibangbee, 2016).

1.4.1.1.1 SCBs

SCBs are mainly utilised to enhance the quality of the electrical power systems and improve the power system performance. Such banks are used in transmission or distribution systems to ensure that the lagging PF is close to unity. Furthermore, the harmonics are filtered, and the voltages are maintained in stable conditions by locating the SCB on the distribution feeders. In industries and substations, shunt capacitors are usually situated close to the load terminals. SCBs are usually connected to the power system during the overload condition where the loads drag the inductive current. The SCBs produce VARs to compensate the reactive power. These banks are usually connected to the system when the demand on the Kilo Volt Ampere (KVA) on the distribution line is increased, and the voltages on the buses are decreased (Samineni et al., 2010). SCB is considered an effective way to reduce the power consumed by the feeders. Thus, the inappropriate placement of the SCBs will reduce system efficiency and even harm the entire control system. The appropriate location and optimal size of the SCB must be specified in the distribution system to obtain the maximum benefits from the capacitors (Devabalaji et al., 2018). Nowadays, many techniques and optimisation algorithms have been presented to investigate the optimal placement of capacitors (Mohamed et al., 2015). Mohsin et al. (2016) proposed the optimal allocation and sizing for the capacitor banks to solve the voltage drop and overall losses in the power system. The presented method is tested on realistic 33 kV RDS. Mahesh et al. (2017) proposed a strategy for the optimal allocation and sizing of capacitor banks, as well as renewable DGs, such as solar, wind and biomass in RDS. The proposed technique is examined on the IEEE 33-bus system. The results showed that the proposed methodology is effective in reducing the power loss whilst enhancing the profile. Devabalaji et al. (2015) proposed a new integrated approach for the optimal placement and sizing of the SCB in the radial distribution to solve the power loss issue. The presented technique is tested on the IEEE 34-bus and 85-bus RDS considering all load potentials varying from 50% in light load until the load reaches 160% with 1% step size. Montazeri and Askarzadeh (2018) discussed the capacitor placement in the distribution system considering the power loss index to specify the potential busses for allocating the capacitors in the distribution network. The presented technique is tested on the IEEE 34-bus and 68-bus RDSs with different load factors. Araujo et al. (2018) explained the placement technique for the capacitor banks in the unbalanced distribution system considering the daily load with different levels. The proposed technique focused on calculating the reactive power demand to minimise the losses apart from the discrete capacitor allocation. The simulation results were obtained from several IEEE test systems, such as 4-bus, 123-bus and NEV test feeders.

1.4.1.1.2 TCT

Voltage deviation association with large line impedance causes power loss. Thus, the use of TCTs is considered an effective method in regulating voltage and decreasing losses. Hussain et al. (2017) proposed a technique for minimising the power loss in the distribution systems by using a TCT. The research is presented through a number of investigations to create an auto-generated load profile for the IEEE 69-bus system for every minute for 24 h. The simulation was performed at the optimal tap transformer position and capacity. These authors prospected that the electronic TCT solution would be the present and future equipment for the voltage regulation in the power system. The study is applied on distribution transformers, which comprise the layout design for accessing the terminals of the tap transformer in addition to the estimation of the voltage and current transients. Kabiri et al. (2015) presented a study to help manage the voltage profile and minimise the feeder losses by using a TCT combined with PV distribution generators. The research considers various factors, such as line impedance, dynamic TCT, different load factors and PV penetration levels. The achieved results illustrate that the integrated techniques can organise the voltage during a 24-hour period efficiently. Sarimuthu et al. (2016) proposed a review on the different schemes for the on-load tap changer (OLTC) voltage control to regulate the voltage in distribution networks, including renewable energy resources. Zhang et al. (2016) discussed the real-time active control and reactive power adjustment in the power system by using a TCT with controllable loads. A technique is presented to help the operator adjust the OLTC positions at the connected buses for regulating the reactive power. Accordingly, the overall load control scheme is decentralized.

1.4.1.1.3 DGs

In the new millennium, large fossil fuelled power plants are being replaced by distributed nonconventional/renewable energy resources as alternative energy sources, such as natural gas, wind power, solar photovoltaic (PV) cells and fuel cells, in addition to the combined heat and power (CHP) systems. This phenomenon is due to the load prompt revolution and fossil fuel depletion. DG is considered an effective solution for the voltage control issue to preserve it at its acceptable limits and maintain the delivery of power to the customers. Refereeing to (Senjyu et al., 2018) a technique to control the reactive power depending on the demand resource (DR) programme for obtaining a stable energy network where the clients can obtain a decrease in the power cost by generating a reactive power through the DG. By contrast, the utility grid can acquire a decrement in their power distribution losses. Meanwhile, Aly et al. (2014) analysed the effect of implementing a large-scale PV system on voltage stability and adjustment. Voltage profiles are evaluated by calculating the load flow with different load levels during a 24-h scale. The power flow analysis is accomplished using a forward/ backward sweep technique. Voltage profiles are adjusted by using the PV interface inverters. The voltage nodes are used in the inverter capacity. The study investigated the probable scenarios of voltage collapse in various times. The improved techniques are tested on the IEEE 33 bus system. The results illustrate that the PV interface invertors promote the voltage profile and enhance the power network operation in addition to the OLTC lifespan expansion by decreasing the number of the tap positing. Castro et al. (2016) discussed a novel method called optimal coordinated voltage control (OCVC) to determine a solution for the voltage regulation issue at the buses and generators and the reactive power losses in the distribution system. A comparative study between the OCVC and an ordinary technique for centralised voltage control is examined on the IEEE 13 and 34 bus test with unbalanced system load. According to Jeong et al. (2017), a new equivalent method presented for a low voltage system that contained distributed generators to show the DG effect on voltage and the power flow in LV and medium-voltage systems. The presented method is improved depending on the analytical strategy that allows solving the voltage-reactive power problems by applying a deterministic algorithm. Li et al. (2019) discussed a technique for controlling the local voltage and the reactive power in DGs. The presented method is based on local measurement, which can rapidly respond to the repeated variation of the DG and enhance the performance of the active distribution network. The results are tested on the IEEE 33 bus and 123 bus systems. The reactive power adjustment with different control methods has been utilised in (Qamar et al., 2017) to regulate the voltage in the PV systems with grid-connected mode. The effectiveness of the PV inverters in controlling the reactive power is observed when the inverter's apparent power is considered. This research illustrates such scenario through the rush hours to ensure that the power generation is high, and the voltage rise at the point of common coupling (PCC) reached the maximum. The inverter's capability to supply the necessary reactive power is limited to the inverter's apparent power. Another reactive power resource should be utilised apart from the PV system to compensate for the reactive power during the peak periods.

1.4.2 Optimisation Techniques

Many methods, such as tap changing transformers, capacitor banks and DGs, are used to compensate the reactive power and regulate the voltage. Despite the effectiveness of these components, specifying their optimal size and position is still a challenging task. Several optimisation methods have been improved to determine the appropriate placement and capacity of the reactive power resources. These methods can be divided in four main categories: heuristic approaches, analytical techniques, numerical programming methods and artificial intelligence (AI)-based algorithms. Enhanced stochastic approaches compensated the time consumed in the analytical optimisation techniques, especially with the complex tasks, to apply a convenient method. Consequently, various optimisation algorithms, such as simulated annealing, dynamic programming, GA, tabu search, evolutionary programming, ant colony system, PSO, fuzzy-based optimisation algorithm, shuffled frog leaping algorithm and honey bee mating optimisation, have been examined (Ali et al., 2017). Although the heuristic techniques cannot guarantee a global optimal resolution, acceptable close to optimal solutions with permissible calculation period have been attested (Araújo and Uturbey, 2013). Several heuristic strategies have been used to overcome the optimal size and location of the reactive power resources. Mohamed et al. (2018) presented a hybrid technique called genetic moth swarm algorithm (GMSA), which adapted a GA apart from the MSA. This technique aims to reduce the losses and overall expenses of the power system in addition to enhancing the voltage profile of the network under different load conditions. The results have been tested on the IEEE 33 node and 69 node systems. George et al. (2018) utilised an optimisation method called ALO to determine the optimal capacity of the VARs and the optimal position of the fixed capacitors in medium and large RDSs. The suggested technique is applied on the IEEE 33 node and 69 node test systems. Ali et al. (2017) utilised the loss sensitivity factors to specify the appropriate buses for connecting the DG in addition to the ALO, which was used for allocating and sizing the DGs on the elected buses. In addition to the Wilcoxon test system, the presented technique is examined on two IEEE bus systems.

1.4.3 Heuristic and Meta-Heuristic Investigation Techniques

In contrast with the analytical techniques utilised to resolve optimisation issues and those that can assure an optimum resolution to the optimisation challenges if they occur, heuristic approaches only aim to provide a quite good solution, which is not certainly the global optima (Marti & Reinel, 2011). Heuristics are classified as problem-relay on principles that combined with an investigation method that can be utilised in optimisation. These types of investigation methods are generally named as greedy techniques. A greedy method investigates the resolution domain of a specified function by solo seeking for the optimal one at that time according to a predetermined heuristic standard.

Meta-heuristics refer to upper-level issue-individualistic algorithms that support a group of techniques or instructions to improve an investigation procedure for optimum resolutions compared with heuristics. These algorithms avert benefit from the available information of the resolution area. Accordingly, such algorithms can extensively investigate within the resolution domain. Meta-heuristics frequently permit decay of the acquired resolutions to inspect a diverse resolution area.

According to Martí and Reinelt (2011) who stated that various motives for the alternative use of heuristic optimisation techniques can be utilised as conventional deterministic strategies:

No available technique can resolve the issue. Examples comprise of the optimisation of non-differentiable or non-convex functions, discrete feasible space and objective functions with several local maxima or minima. Heuristics are also beneficial when the mathematical model derivations are either impossible to calculate or unrecognised.

1.4.4 Meta-Heuristic Investigation Algorithms

In the precise problem of the DG placement and sizing, causes were discovered in the literature owing to the utilisation of a meta-heuristic investigation technique of an exact numerical algorithm:

- The equations of power balance for the power flow issues are nonlinear and non-convex.
- Generators nonlinear and non-convex have specifications (Yuan, 2009). Non-convexities of the issue modulation make mixed integer nonlinear programming (MINLP) insufficient to be applied to problems because of the algorithm converging risk to fill in the local optimal alternative of the global optima.
- The nonlinearity of generator cost curves can be considered convex and soft functions (Kumar & Gao, 2010).
- The dependencies of the multi-period state need a long execution period of time to resolve the issue with MINLP. Soares et al. (2013) highlighted the execution time of a meta-heuristic approach compared with MINLP. The researchers reported that MINLP needs 25.5 h to resolve the scheduling of DG generation during a 24-h period inclusive storage strategies compared with the meta-heuristic approach that only assumes 30 s. Moreover, the researchers reported a variation in the optimal amount considering a cost function of 0.9% in the meta-heuristic investigation technique.

1.4.4.1 PSO

PSO is considered a meta-heuristic method that has received great attention because of its effectiveness in resolving complicated challenges. This method is well known as a robust technique in solving issues with special specifications, such as nonlinearity, high dimensionality and non-differentiability. Ramadan et al. (2017) adapted such method for determining the optimal placement of the capacitors to minimise the power losses and manage the voltage profile in the distribution systems that comprise wind turbine energy generators. The solution formulated a non-linear cost fitness function because of the non-linear feature of the system due the wind turbine generators. The PSO simulation is applied on the IEEE 16 bus and 30 bus test systems, and it proved its robustness compared with the GA. Silva et al. (2017) adapted a modified PSO (MPSO) technique to size the PV panels for minimising the power losses and enhancing the voltage profile in the power system. The presented method was tested on the IEEE 13 node feeder system in addition to the micro-grid of the Federal University of Paraiba. The proposed method proved its robustness and effectiveness in achieving the objective functions. Mohamed et al. (2016) proposed a technique to specify the optimal capacity for the hybrid renewable energy network by using a load management application for the smart grid according to accessible generators. This technique aims to maximize the system production and achieve the load needs with low cost and optimal reliability. The system consists of PV panels, storage batteries, wind turbines and diesel generator as backup power sources. The capacity of the system elements is specified using PSO. The simulated results are applied on the far distant areas in Saudi Arabia.

In these meta-heuristics population-based techniques, such as GA and PSO, a large number of non-controllable resolutions can be obtained from a sole execution because of their multipurpose search capacity. The capabilities of these techniques are limited to dimensionality issues. Furthermore, no convergence is guaranteed; thus, robustness is weak.

1.4.5 Objective Functions and Constraints

Single or multiple objective functions have been used combined with system constraints to increase the profit from reactive power incentives. Generally, the regulation of voltage profile and the minimisation of real and reactive power losses are considered essential objectives in distribution systems. Several additional objectives may incorporate with the base objectives to achieve the optimal performance of the system; These objectives include expense minimisation or profit maximisation, increase in the MVA capacity of the system, maximisation of the size of the reactive power resources, generation of index-based functions and decrease in the current of weak feeders (Pesaran et al., 2017). The main purpose of constrains in optimising the power systems is to guarantee the achievement of the design and operation conditions under the specified limitations. Various types of power network maintenance constraints include the PF, bus voltage, feeder current and power balance. By contrast, the interior power capacity, short circuit current and transformer capacity are common models of the power plant conservation constraints that have been inspected by research papers.

In 2017, multi-objective optimisation has been utilised to specify the optimal location of DGs. Active and reactive power losses, voltage fluctuation and total cost are the objectives of the module. The optimal placement and sizing of the DGs are determined by PSO incorporated with fuzzy decision-making technique. The proposed method proved its effectiveness on the IEEE 69 node RDS. Mendoza et al. (2019) introduced a technique based on PSO to overcome the optimal placement and capacity of the capacitors in the power distribution system. The multi-objective functions that have been utilised are real power reduction and operational and constant costs, thereby enhancing the voltage quality. The proposed approach was examined on the IEEE 34 node and 84 node test radial distribution networks.

1.5 Scope and Limitation of the Research

This thesis aims to optimise the placement and capacity of the DGs in the power system by using the ASO algorithm. Two tested systems, namely, IEEE 33 bus RDS and IEEE 14 bus system, are considered to evaluate the performance of the proposed technique. 1, 2 and 3 DGs are synchronous generators that inject real and reactive powers to the system and operate at a PF of 0.866. These generators were used as case studies to apply the optimisation and obtain the optimum DG location and size. The backward–forward sweep and NR computational methods are applied to compute the power losses, voltage magnitudes and other parameters. The ASO algorithm, which is a newly developed meta-heuristic optimisation technique, is adapted to minimise the problem and obtain the optimal size and location of the DGs in the power network systems. The results of the presented technique are compared with the GA-PSO algorithm to validate the preciseness and effectiveness of the proposed strategy.

1.6 Benefits of Research

This thesis addresses the significance of the contribution of DGs in the power systems in terms of power loss minimisation, voltage profile improvement (VPI) and operating cost reduction. The optimal capacity and allocation of DGs can be determined by using ASO, which is an effective and efficient technique for the actual implementation of DGs in the power systems. The acquired results display a reliable optimal resolution that reflects the important cooperation between the theoretical background and the real-life practical application. Such results pave the way for other researchers to investigate future work in this topic and help improve the reliability and quality of clean electrical power systems.

1.7 Thesis Outline

This thesis is structured into five chapters. Chapter 1 presents an introduction to the research, including overview, problem statement, objectives, scope and research limitations, research benefits and thesis outline. Chapter 2 provides a description for the optimisation that handles a multi-objective problem, including the objective functions and constraints. The methods and materials utilised in this research are presented with description of the power flow methods that are used in the tested systems. The other optimisation techniques utilised in this study are presented. The proposed optimisation technique with details about the principles of this method and the manner by which it is implemented to solve the optimisation problem is presented. Chapter 3 shows the simulation results of the multi-objective optimisation along with the discussion of the obtained results. Chapter 4 is final chapter of the thesis, and it summarises the conclusion and discusses the future work related to DGs.

1.8 Chapter Summary

This chapter discusses the related problems and targets at supplying general details about the distributed power generation in the electricity market competition. Generally, DG is defined as the electric power generation inside power networks or on the consumer front of the network. Distributed resources, distributed utility and optimisation techniques also are discussed.

Chapter 2: Methodology

2.1 Introduction

This section illustrates the mechanism by which a recently invented novel optimisation algorithm called ASO, which is inspired by MD, efficiently solves a complex optimisation challenge. Power loss minimisation and sustainment of the system voltage profile within the acceptable limits with the adequate application cost reduction are considered the fitness functions for a multi-objective approach used for DG optimal capacity and location in the power systems. In the proposed model, one single operation point has been used to demonstrate the load in the system.

2.2 Materials and Methods

This section presents the methods that are used in the study, as well as the materials that are utilised to achieve the research objective.

2.2.1 Power Flow using Newton–Raphson (NR) Method

The study of load flow is a basic analysis for the power system that provides information about the loading and losses of the line and transformer in addition to the voltages at different points in the system. Subsequently, the work on electric power, which increased the low voltage level, began at the end of the 19th century (Eltamaly et al., 2018). The interconnected network of delivering electricity or the electrical grid was extended and classified as generation, transmission and distribution that increase the transmission voltage to 1200 kV. This complexity increases the number of problems in power flow control, and a plan is required to reach the minimum cost without affecting the voltage in the system. The state of the power system and the calculations of its power that flows through the lines are important for the future expansion of the system. Consequently, studies have been carried out to develop computer programmes for the load flow analysis of large power systems (Wende et al., 2008). Different methods for calculating the load flow are performed. However, this research focuses on the NR method.

NR has many advantages, such as low computation time and powerful convergence characteristics or sure convergence; this method is used to solve nonlinear algebraic equations (Sharma et al., 2017). The power flow equations are as expressed as follows:

$$P_i(Real\ Power) = |V_i| \sum_{j=1}^{m} \left(|V_j||Y_{ij}|cos(\emptyset_{ij} + \delta_j - \delta_i)\right), \quad (2.1)$$

$$Q_i(Reactive\ Power) = -|V_i| \sum_{j=1}^{m} \left(|V_j||Y_{ij}|Sin(\emptyset_{ij} + \delta_j - \delta_i)\right). \quad (2.2)$$

Where:

V_i = Voltage at the *i*th bus

V_j = Voltage at the *j*th bus

Y_{ij} = Admittance of the *i*th and *j*th buses

$\emptyset_{ij=}$ Admittance angle

$\Delta_j =$ Phase angle of the *j*th bus

$\Delta_I =$ Phase angle of the *i*th bus

Jacobean matrix J is used to solve the NR method:

$$\boldsymbol{J} = \begin{bmatrix} \frac{dp}{d\delta} & \frac{dp}{|V|} \\ \frac{dQ}{d\delta} & \frac{dp}{|V|} \end{bmatrix}. \quad (2.3)$$

Yij is the bus matrix:

$$\boldsymbol{Y_{bus}} = \begin{bmatrix} Y_{11} & \dots. & Y_{ij} \\ \dots. & \dots. & \dots. \\ Y_{ji} & \dots. & Y_{jj} \end{bmatrix}. \tag{2.4}$$

The load flow minimises the mismatch between:

- The actual injected power and the calculated values.
- The reactive injected power and the calculated values.

Accordingly, the iteration must be used to estimate the bus voltages and their angles for calculating mismatches. A small number of mismatch indicates that the load flow is converged. Before the iteration process (*r*th) is initiated, we will consider one bus as a slack bus in the system that has the voltage of one and phase of zero. We also assume other buses, such as PQ (load bus) and PV (generator).

$$P_i^r = |V_i|^r \sum_{j=1}^{m} \left(|V_j||Y_{ij}|cos(\emptyset_{ij} + \delta_j - \delta_i)\right), \tag{2.5}$$

$$Q_i^r = -|V_i|^r \sum_{j=1}^{m} \left(|V_j||Y_{ij}|sin(\emptyset_{ij} + \delta_j - \delta_i)\right). \tag{2.6}$$

We let

$$e_i^r = |V_i|^r cos\delta_i^r \quad and \quad f_i^r = |V_i|^r sin\delta_i^r, \tag{2.7}$$

$$nhj\ G_{ij} = |Y_{ij}|cos\emptyset_{ij},$$

$$B_{ij} = |Y_{ij}|sin\emptyset_{ij}.$$

Subsequently, ΔP_i^r and ΔQ_i^r are calculated to obtain values that are less than the tolerance, and the iterations are stopped.

$$\Delta P_i^r = P_i(scheduled) - P_i^r \ \ for\ PV\ and\ PQ\ buses, \tag{2.8}$$

$$\Delta Q_i^r = Q_i(\text{scheduled}) - Q_i^r \text{ for PQ buses.} \quad (2.9)$$

The solutions of P1 and Q1 are determined. However, if convergence is not obtained, then Jacobean matrix elements will be calculated. Thereafter, the voltage magnitude and phase angles are performed. The iteration process continues until convergence is obtained. The voltage magnitude and phase angles are updated as follows:

$$|V|^{(r+1)} = |V|^r + \Delta|V|^r, \quad (2.10)$$

$$\delta^{(r+1)} = \delta^r + \Delta\delta^r, \quad (2.11)$$

The NR method is the preferred general approach for solving the power flow problems in large systems. This method has been selected because of to its speed, computation time, convergence characteristics and storage.

2.2.2 Power Flow Using Backward–Forward Sweep Method

In the RDSs, reiterated methods are generally utilised when the investigation of power flow in transmission systems are inappropriate because of their computational characteristics and convergence properties. Gauss–Siedel and NR methods are common in transmission systems. Nevertheless, these approaches are inconvenient for distribution systems because of the increased R/X rate and the presence of off-balanced load. The characteristics of the distribution systems cause the unhurried convergence. Accordingly, exceptional techniques are required to resolve the load placement issues immediately.

The forward–backward method is an iterative approach used for analysing the power flow in radial distribution networks. Two phases of computation are implemented in every iteration. The sets of recursive equations are utilised to solve the load flow iteratively. Power flow is calculated by solving the first set of equations in the backward direction. The power flow is tracked down from the load to the source. In the backward sweep, the solution of the current and power is obtained with the possible updates of the voltages (Rupa and Ganesh, 2014). The voltages obtained in the forward sweep are kept constant during the backward sweep. The magnitude and angle of the voltage drop are calculated using the second set of equations in the forward direction where the path leads from the source to the load. In forward sweep, the current values are updated along with the power flow at each node based on the calculated voltage drop. The substation feeder voltage is assigned as the actual value of its voltage. The value of the effective power that is obtained from the backward sweep should be kept constant during the forward sweep in each branch. In the forward–backward sweep, the electric quantities of the backward propagation affect the three variants that can be obtained using the following:

1. The branch current refers to the summation of the currents in that branch.

2. The power flow refers to the summation of the powers in that branch.

3. The admittance summation method is used node by node to obtain the driving point admittance.

These variants are homogeneous in forward propagation. The calculation of the bus voltages begins from the source node to the last node based on backward sweep calculations. The quantities used in backward sweep update the voltages after several iteration steps, and the iteration process stops when convergence is obtained. Consequently, a comparison occurs between the calculated values and the previous iteration values. Convergence is obtained when the difference between the new and old values is <0.0001 (tolerance value). If convergence is not obtained, then the iteration process continues. The new values of the power flow will be calculated by backward propagation. The process will stop when the solution cannot to meet the convergence standards. At present, the backward–forward method has been reformulated for the analysis of the iteration process convergence. Effective power flows can be calculated by backward propagation for a branch in between nodes 'k' and 'k+1'. The effective real and reactive powers are calculated as follows:

$$P_k = P'_{k+1} + r_k \frac{(P^2_{k+1} + Q^2_{k+!})}{V^2_{k+1}}, \tag{2.12}$$

$$Q_k = Q'_{k+1} + X_k \frac{(P^2_{k+1} + Q^2_{k+!})}{V^2_{k+1}}. \tag{2.13}$$

P'_{k+1} and Q'_{k+1} can be obtained by using the following equations:

$$P'_{k+1} = P_{k+1} + P_{Lk+1}, \tag{2.14}$$

$$Q'_{k+1} = Q_{k+1} + Q_{Lk+1}. \tag{2.15}$$

In the previous equations, P_{k+1} is an effective real power from the $\mathrm{k} + 1$ node, and Q_{k+1} is an effective reactive power from the $\mathrm{k} + 1$ node.

The voltages and angles are calculated in the forward propagation. If the voltage at k is $V_k < \delta_k$, then the voltage at $k + 1$ is $V_{k+1} < \delta_{k+1}$. The impedance between k and $k + 1$ node is defined as $z_k = r_k + jx_k$. Thus, the current in the branch is presented as follows:

$$I_k = \frac{V_k < \delta_k - V_{k+1} < \delta_{k+1}}{r_k + jx_k}. \tag{2.16}$$

Recursive equations are used to obtain the nodal values of the voltages and angles. In the first iteration, the voltage is assumed to be 1 pu at all nodes.

Algorithms:

In the first step, the distribution system bus data are read along with their line data, apparent power and base voltage. The injected active and reactive powers are then obtained using

$$P_{inj} = P_{gen} - P_{load}, \tag{2.17}$$

$$Q_{inj} = Q_{gen} - Q_{load}. \tag{2.18}$$

Next, the value of iteration counter k is set to be one. The convergence can be determined by setting $\varepsilon = 0.001$, $\Delta P_{max} = 0$ and $\Delta Q_{max} = 0$. Thereafter, the value of the injected nodal current can be evaluated at node i by using the following equation:

$$I_i^{(k)} = \left(\frac{S_i}{V_i^{(k-1)}}\right)^* - Y_i V_i^{(k-1)} \quad where\ i = 1,2,\dots,n. \tag{2.19}$$

The branch current can be obtained using KCL after the backward sweep is applied. Forward sweep is applied to obtain the voltage at each node by using KVL. The injected power at i can be calculated using the following expression:

$$S_i^k = V_i^k (I_i^k)^* - Y_i \left|V_i^k\right|^2. \tag{2.20}$$

Then, the convergence is checked. If $\Delta P_{max} \le \varepsilon$, and $\Delta Q_{max} \le \varepsilon$, then the process is stopped. If the condition is not satisfied, then we set $k = k + 1$ and calculate the injected nodal current again until the condition is satisfied.

1) The backward–forward sweep method merits are presented as:

a) The Jacobean matrix is unnecessary.

b) This method does not rely on PV bus (voltage controlled node) and the number of DGs for small networks

c) This method is convenient for online and offline issues

2) Drawback of backward–forward sweep method:

a) Failed in dealing with heavy load

b) Unsuitable for large-scale systems

Consequently, backward–forward sweep method acquires excessive speed, has sturdy convergence and requires less memory.

2.3 DG Types

DG units are categorised into four types depending on their ability to transfer the active and reactive power energy of the distribution system (Hung et al., 2010). In this research, only one type of DG, that is, PQ type (e.g. synchronous generator), is considered. Under this type, the generation units can deliver real and reactive powers of 2000 KW and 80 MW. The PF is constant at 0.866. In Hung et al. (2010), α is

$$\alpha = sign\big(\tan\big(cos^{-1}(PF)\big)\big). \tag{2.21}$$

The sign (+1) means that DG is providing reactive power, whilst (−1) means that DG is absorbing reactive power. Thus, the output reactive power of the DG is

$Q_{DG}^{k} = \alpha \, . P_{DG}.$

In this DG type, $\alpha = (+1)\big(\tan\big(cos^{-1}(PF_{DG})\big)\big),$ (2.22)

$$Q_k = Q_{DG}^k - Q_D^k, \tag{2.23}$$

Where

Q_k is the net reactive power at node k,

Q_{DG}^k is the DG reactive power at node k,

Q_D^k is the demand reactive power at node k, and

PF_{DG} is the DG PF.

2.4 Optimisation Algorithms

Majority of the power systems have non-convex nonlinear optimisation issues where ordinary optimisation techniques, such as gradient-based methods end with local optimal solutions. The solutions obtained from traditional optimisation techniques are strongly based on the initial values of the methods. The meta-heuristic or global optimisation algorithm is proposed in this thesis to eliminate these issues. This algorithm can guarantee acceptable results. Generally, gaining the global optima solutions needs abundance of running duration and assets. The algorithm does not work if the solution is unsatisfied and no significant enhancement has been performed. Consequently, if the obtained results are quite close to the optimal global resolution, then it can be accepted as the optimal solution for the problem.

Within the global optimisation algorithm, several compromises, such as raising the objective functional weights to avoid the local optima, have to take place. A number of iterations should be initiated with no bias to assure that the algorithm reached the global optima.

Two optimisation algorithms have been presented in the following parts (GA-PSO and ASO). These optimisation techniques are easy to simulate and appropriate for solving the power system issues.

2.4.1 GA

GA is an unsystematic search optimisation technique inspired by Darwinian Theory. This technique is a specific category of the evolutionary techniques that utilise methods influenced by the biological revolutionaries, such as inheritance or population, exploration, election and exploitation (also named as recombination) (Martin and Spears, 2001). GA initiates the inspection from a series of population that is nominated to be the proper solutions randomly set within the inspection limits. With the natural growth, this technique will improve the new prospect resolution named as off-springs from preceding parents. The objective of each solitary in the population is assessed in every generation. Numerous solitaries are elected from the present population (depending on their fitness) and adjusted to format a new novel population. The recently elected population is in the updated iteration of the technique. The technique terminates in one of these cases, hit the maximum generation number or reach the best fitness quantity (Voratas, 2012). GA, which procures to an undesirable poor convergence and inadequate robustness, is considered a limited algorithm for research characteristics. Consequently, adapting this method in complex issues will potentially lead to trapping within the local optima.

2.4.2 PSO

PSO is considered a recent evolutionary strategy attributed to Eberhart and Kennedy (1995). This approach is a meta-heuristic stochastic global method based on the candidate solution population. Moreover, PSO is basically inspired by the social behaviour of the organised movement of the flock of birds or school of fish in their journey for hunting food. In this technique, the particles move to many directions in the search space where each of them represents a candidate solution. Each particle consists of the control variable data and is incorporated with others with their optimal data that specifies its performance in the fitness domain. Each swarm k contains its placements *Yk = (yk, 1, yk, 2,…, yk, Mv)* where *Mv* denotes the control variable numbers, *Vk* is the *velocity = (vk, 1, vk, 2, …, vk, Mv)* and local (personal) optimal experiment *Ypbestk= (ybest1, ybest2, …, ybestMv)*. In every iteration, each particle transforms in its own local optimal location provided and towards the global optimal location specified by the swarm particles. The following equation represents the particle operation:

$$V_k^{it+1} = w^{it} \times V_k^{it} + AC_1 \times rand_1 \times \left(X_{pbestk}^{it} - X_k^{it}\right) + AC_2 \times rand_2 \times \left(X_{gbest}^{it} - X_k^{it}\right) \quad (2.24)$$

$$X_k^{it+1} = X_k^{it} + V_k^{it+1}, \quad (2.25)$$

Where V_k^{it+1} represents the particle's k velocity at the *it +1* iteration; V_k^{it} is the particle's k velocity at it iteration; AC1 and AC2 are constants of the acceleration; rand_1 and rand_2 represent a random values within the range of 0 and 1, respectively; X_{pbestk}^{it} is the local optimal location of particle k at it iteration; X_k^{it} represents the placement of particle *k* at *it* iteration; X_{gbest}^{it} performs the optimal global location amongst the whole particles at *it+1* iteration; and X_k^{it+1} formulates the location of particle *k* at it iteration.

In nonlinear complex optimisation issues, attaining the optimal resolution using PSO is not guaranteed. Filling in the local minima, which can procure the inclination premature convergence and poor robustness, is easy.

2.5 General Form of Optimisation

The mathematical model for any optimisation problem can be formulated as:

$$\min \quad \mathcal{F}\,(E\,,X), \tag{2.26}$$

$$G = 0,$$

$$\mathbb{Q}_{min} \ \leq \ \mathbb{Q} \ \leq \ \mathbb{Q}_{max},$$

Where $(E\,,X)$ represents the objective function; E is the output; X is the corresponding input; $G = 0$ is the equality constraints; and $\mathbb{Q}_{min} \ \leq \ \mathbb{Q} \ \leq \ \mathbb{Q}_{max}$ is the inequality constraints, where $\mathbb{Q}_{min}/\mathbb{Q}_{max}$ are the limits between min/max for the inequality constraints.

2.5.1 Objective Functions

The proposed multi-objective system aims to improve the power system through the following functions.

- VPI
- Active power loss reduction
- Minimum operating cost

Some objective functions have to be achieved whilst satisfying the system constrains to accomplish the previously mentioned purposes.

- VPI

VPI is considered the first fitness function that needs to be minimised to increase the bus and line stability by captivating the voltage deviation of the bus from the reference node. The effectiveness of the voltage profile of the nodes after adding the DG to the system is measured by voltage deviation index (VDI), as shown in the following formula:

$$Min\ VPI = VDI = \frac{\left|\sum_{k}^{nbus} V_{DG} - V_{k,ref}\right|_{WDG}}{\left|\sum_{k}^{nbus} V_{base} - V_{k,ref}\right|_{WoDG}}, \tag{2.27}$$

Where V_{base} represents the voltage magnitude in pu at the buses without DG, V_{DG} is the voltage magnitude in pu on the nodes with DGs, and $V_{k,ref}$ is the voltage reference, which is in this case is 1.

- APL

APL is the second fitness function that represents the effectiveness of the inclusion of the DGs on the active power loss. After the addition, this function is usually measured using the active power loss index (*APLI*) depicted by the following equation:

$$Min\ APL = APLI = \frac{\sum_{i}^{nbus} Pl_{DG}}{\sum_{i}^{nbus} Pl_{base}}, \tag{2.28}$$

where Pl_{base} represents the power loss before adding the DGs to the system, and *Pl* denotes to the power loss after adding the DGs.

Moreover, *Pl* can be calculated using Equation (2.29)

$$Pl = \sum_{b}^{Nb} I_b^2\, R_b\, L_b\,, \tag{2.29}$$

Where *Pl* is the total power loss in all the lines in the system in pu, *I* represents the current value of the branch b in pu, *L* is the length of the line in *Km*, *Nb* is the total number of the branches and *b* is the branch number.

- Reduction of application cost (RAC)

The system operating cost consists of several aspects, namely, operating, investment and maintenance costs. In distribution systems, the integrated DGs will fetch an interest to the grid to produce power that substitutes the conventional power energy. Therefore, the generation cost for the DGs should be considered when calculating the network operating cost. Thus, the investment C_{in}, maintenance C_{main}, and generation C_{gen} costs displaced by DGs are considered for the network operating cost (Equation (2.30)):

$$min\ RAC = RACI = \frac{C_{in} + C_{main} - C_{gen}}{(C_{in} + C_{main} - C_{gen})_{max}}. \tag{2.30}$$

Gopiya et al. (2015) utilised several strategies to compute the indices of the investment and maintenance costs. In this study, the cost of investment C_{in} is expressed as Formula (2.31), and that of maintenance C_{main} is calculated as Equation (2.33). The generation cost C_{gen} substituted by DGs is depicted as equality (2.34).

$$C_{in} = \sum_{k}^{M} \alpha_k\ E\ .P_{kmax}\ .\ C_{pui}\ .\ \frac{d(1+d)^{LTDG}}{d(1+d)^{LTDG-1}}\ , \tag{2.31}$$

where C_{pui} denotes to the pu size of the investment cost of the DG at bus k; M represents the number of candidate DGs; $\alpha_k = \mathcal{F}(x_1, x_2, x_3)$ is the weighting factors of the investment cost, where x_1 depends on the environmental coefficient, x_2 is the displacement coefficient and x_3 is the cost of labor and transportation coefficients; d represents the discount rate; $LTDG$ is the DGs life time; P_{kmax} form the maximum capacity value of the DG in candidate bus k; and E is the candidate DG size in the candidate bus k. Variable E is depicted by Equation (2.32) by normalising the capacity:

$$E = \frac{P_k}{P_{k,max}}\ \ ,\ k = 1,2, \ldots, M, \tag{2.32}$$

$$C_{main} = \sum_{k}^{M} T_{MH}\ .\ C_{pum}\ .E\ .\ P_{kmax}. \tag{2.33}$$

Where T_{MH} is the maximum DG generation hours, M is the DG number and C_{pum} represents the pu capacity for the maintenance cost of the DG at bus k.

$$C_{gen} = \sum_{k}^{M}\ E\ .\ P_{kmax}\ .\ \eta_k\ .\ T_{eqh}\ .\ C_{pug}\ , \tag{2.34}$$

where T_{eqh} represents the hours of the equivalent generation of the DG generations, C_{pug} is the electricity cost of the unit-grid of the DG, η_k is the DG efficiency at bus k, and $(C_{in} + C_{main} - C_{gen})_{max}$ represents the values using the maximum capacity size of the DGs.

2.5.2 Multi-Objective Functions (MOFs)

A multi-criterion method is used to simultaneously optimise more than a single fitness function, which can be resolved by using the weighting factors for maximising the objectives of the DG where a tiny regulation can cause a huge shift in the optimal method behaviour.

In this research thesis, two and three objective functions are used to solve the problem of placing and sizing the DGs in the power networks, respectively.

The fitness function of the system is calculated using Equation (2.35).

$$MOF = W_1.VPI + W_2.LPL + W_3.RAC \, , \tag{2.35}$$

wherein $0 \leq W \leq 1$ and $\sum_k^O W_k = 1$, (2.36)

where W1, W2 and W3 represent the weighting coefficients for VPI, LPL and RAC, respectively. The fitness functions specify the weight value based on the importance of every function to the system where the valuable one has the highest weight compared to other factors. A normalisation process should be considered because the objective functions are different.

2.5.3 System Constraints

- Inequality constraints
    - DG Generation Capacity

The inequality constraints contain the allowable penetration size for the DGs in the power system and the upper limits of DG size at the nominated bus k. At each candidate bus for the installed DG, the active and reactive powers are restricted by the upper and lower limits as follows:

$$\begin{cases} Pg_{min} \leq Pg \leq Pg_{max} \\ Qg_{min} \leq Qg \leq Qg_{max} \end{cases} . \tag{2.37}$$

Each nation has a restriction on the DG penetration to assure the system reliability. If we suppose that the maximum factor of DG penetration is 30%, then the maximum DG capacity injected to the power system should be ≤30% of the overall real power in the network system. This notion means that

$$\sum_{k=1}^{M} P_{GDK} \leq 0.3 \, . P_{total\ load} \, , \tag{2.38}$$

where $P_{total\ load}$ represents the total load active power in the power network. Variables Pg_{min} and Qg_{min} and Pg_{max} and Qg_{max} are the minimum and maximum real and reactive power for the DGs, respectively.

- Node Voltages

The DG incorporation in the power system boosts the voltage limits on all nodes, which may lead to over-voltage at several nodes. The voltages on all the nodes are restricted by two values, namely, the upper (V_{max}^{k}) and lower V_{min}^{k} limits Equation (14).

$$V_{min}^{k} \leq V^{k} \leq V_{max}^{k} \tag{2.39}$$

Similar to (Hung and Mithulananthan, 2013), the upper and lower levels are taken as 0.95 and 1.05 pu, respectively.

- PF

An inequality constraint PF is based on the ratio P/Q of the generator, where this ratio should be constant. For example, any variation in the real power should be followed by a mutation in the reactive power. Generally, the DG PF should be kept close to uniform to guarantee the full production of the real power of the DGs. Equation (2.40) expresses the PF constraints in the system, where PF_{max} represents the upper limit which equals to one and PF_{min}, which forms the lower limit, should be ≥0.8.

$$PF_{min}^{k} \leq PF^{k} \leq PF_{max}^{k} \qquad (2.40)$$

- Equality constraints
  - Power Balance Constraints

The power balance is an equality constraint where the overall power generation of the system without DG P_g in addition to the power of the DG unites Pg_{DG} should equal to the overall load demand P_d along with the total active power loss P_{loss} Equation (2.41):

$$\sum_{g=1}^{NG} Pg_{DG} + \sum_{g=1}^{N} P_g = P_d + P_{loss}. \qquad (2.41)$$

2.6 Hybrid GA-PSO

A hybrid GA-PSO is combination between a PSO and a GA where the population of the optimal evolution is chosen by the GA; the PSO then optimises the results regardless of the iteration (Sahoo et al., 2014). First, the GA and PSO methods are initialised. Thereafter, both techniques are simultaneously executed, and the optimal solution is stored. After a specific iteration number (stopping criterion), the simulation stops the running and presents the optimal solution as a final result.

The GA-PSO algorithm procedures are shortened as follows (Dufo-López and Bernal-Agustín 2008):

Step 1: Clarify the initial data population size, generations' maximum number, crossover and mutation probabilities and the decision variable bounds.

Step 2: Set *it* = 0, which represents the number of iteration/generation.

Compute the fitness function for each chromosome.

Step 3: Generate the population of the chromosomes and particles.

Step 4: Calculate the objective function for every chromosome.

Step 5: Search for the chromosome/particle global best with the optimal fitness value.

Step 6: Split the chromosomes and particles into two identical sizes of population.

Step 7: Iterate the following until the stopping criterion breaks:

- Add one to the iteration value.
- Apply GA for population, and then crossover to find the new population.
- Discover the optimal chromosome from the present population by comparing the current population with the previous superior one; keep the optimal one as the best chromosome.
- Increase *it* by one.
- Update the new population by applying tournament selection.
- Apply the PSO for particles, and update the optimal location of every particle through comparing the location of the entire chromosomes of the GA populations.
- Calculate every particle velocity, update the new location and obtain the global optimal particle.

Step 8: Printout the location and global optimal particle fitness.

Step 9: End.

2.7 ASO Algorithm

In comparison with the searching technique of swarm intelligent optimisation algorithms, a recent meta-heuristic optimisation algorithm has been invented by (Zhao et al., 2019). The algorithm mimics the physical motion of atoms as illustrated in MD simulation with few parameters to regulate. MD is a method that utilises a computer to imitate the atom growth and molecule location all the time. The atom and molecule movements are fundamentally specified by Newton's second law; Fi and Gi are interaction and constraint forces, respectively, both forces influence the *i*th atom, which has a mass *mi* by the following Formula (2.42) (Ryckaert et al., 1977).

$$a_i \times m_i = F_i + G_i \; . \tag{2.42}$$

In ASO, the location of every atom inside the search domain performs a resolution assessed by its mass, where the preferable solution represents a heavy mass, and vice versa. In the population, the atoms will be attracted or repelled to each other depending on the distance between them, thereby motivating the light ones to attract to heavy atoms. The heavy atoms have minimal acceleration and activate by searching for optimal resolutions in the nearby domain. By contrast, the light atoms with great acceleration seek to detect new promising areas in the whole search domain.

The interaction force amongst two atoms or molecules can be approximately described by Lennard–Jones (L–J) potential as follows:

$$F_{ij}^{d}(t) = \frac{24\varepsilon(t)}{\sigma(t)}\left[2\left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{13} - \left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{7}\right]\frac{r_{ij}(t)}{r^{d}(t)}. \tag{2.43}$$

Thus, the interaction force between the *i*th and the *j*th atoms in the *d*th dimension is formulated as follows:

$$F_{ij}'(t) = \frac{24\varepsilon(t)}{\sigma(t)}\left[2\left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{13} - \left(\frac{\sigma(t)}{r_{ij}(t)}\right)^{7}\right]. \tag{2.44}$$

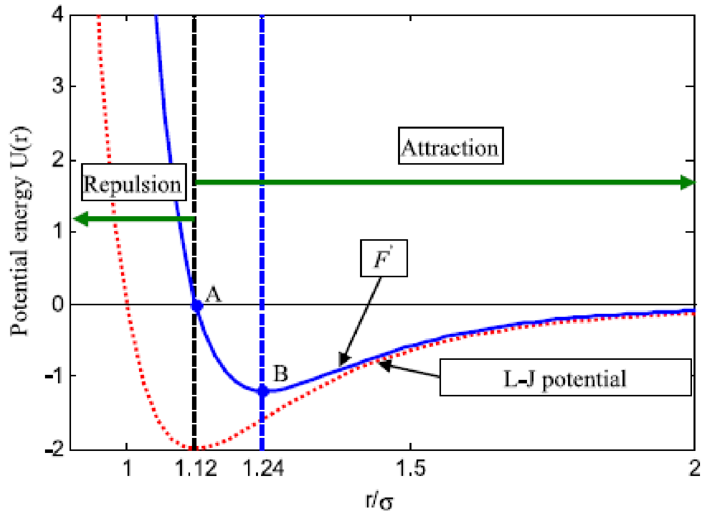

Figure 2: Atom Force Curve

Figure (2) illustrates the force curve of atoms for MD. The atoms maintain a proportional space varying in a specified range all the time due to the attraction or the repulsion. The amplitude alternation of the repulsion is bigger than the attraction, as shown in distance Equation (2.45):

$$r \ = 1.12\,\sigma, \tag{2.45}$$

where ε is the depth function that measures the intensiveness of the attraction between the pair of particles, and σ provides a collision diameter measurement that performs the distance where the inter-particle potential is zero between the two particles Figure (2).

The repulsion is positive, whilst the attraction is negative. This situation leads to the inability of the atom to be convergent to a particular location. Thus, equilibrium (2.44) is unsuitable to resolve the optimisation problem.

A revised version of this equation is established (Equation (2.46)):

$$\mathrm{F}'(\mathrm{t}) = -\eta(\mathrm{t})\left[2(\mathrm{h_{ij}}(\mathrm{t}))^{13} - (\mathrm{h_{ij}}(\mathrm{t}))^{7}\right], \tag{2.46}$$

where $\eta(t)$ represents the depth function to adjust the repulsion or attraction regions and can be written in Equation (44).

$$\eta(t) = \alpha(1 - \frac{t-1}{T})^3 e^{\frac{20t}{T}} , \tag{2.47}$$

where α represents the depth weight, and T is the iteration maximum number. The *h* values ranging between 0.9 and 1.2 belong to the repulsion area. The attraction occurs when *h* varies from 1.12 to 2. The equality appears when *h* = 1.12. As *h* keeps increasing from equality point (*h* = 1.12) until reaching the maximum point (*h* = 1.24), the attraction will gradually increase. Thereafter, *h* begins to decrease. When h is ≥2, the attraction is roughly equal to zero. Thus, h_{min}=1.1 is set as a lower limit of repulsion with a minimal function amount to widen the investigation in ASO. The upper limit of attraction with a greater function rate is adjusted to h_{max} =2.4. Accordingly, *h* is defined in Equation (2.48).

$$\begin{cases} \mathrm{h}_{min} & \frac{r_{ij}(t)}{\sigma(t)} < h_{min} \\ \frac{r_{ij}(t)}{\sigma(t)} & h_{min} \leq \frac{r_{ij}(t)}{\sigma(t)} \leq h_{max} \\ h_{max} & \frac{r_{ij}(t)}{\sigma(t)} < h_{min} \end{cases} . \tag{2.48}$$

The length scale σ(t) is represented by Equality (2.49).

$$\sigma(t) = \left\| x_{ij}(t), \frac{\sum_{jeKbest} x_{ij}(t)}{K(t)} \right\|_2 \tag{2.49}$$

and

$$h_{min} = \mathrm{g}_0 + \mathrm{g(t)} \text{ and } h_{max} = u , \tag{2.50}$$

where *Kbest* is a subset of an atom population comprising of the first *K* atoms with the optimal function fitness values. A drift factor g makes the algorithm diverge from the exploration to the exploitation and is defined as follows:

$$\mathrm{g(t)} = 0.1 \times \sin(\frac{\pi}{2} \times \frac{t}{T}). \tag{2.51}$$

Accordingly, the aggregate force acting on the *i*th atom with random weights in the *d*th dimension from other atoms is represented in Equation (2.52):

$$F_i^d(t) = \sum_{j\epsilon Kbest} rand_j F_{ij}^d(t), \tag{2.52}$$

where $rand_j$ is the random number specified between [0,1].

Newton's third law provides that the *i*th atom exerts an opposite force on the *i*th atom for the similar pair-wise interaction, as expressed by Equation (2.53).

$$F_{ij} = -F_{ji}, \tag{2.53}$$

In ASO, a bond between each atom and the optima one is assumed for easiness. Every atom is controlled by a constraint force from the optimal one. Thus, the *i*th constraint of the atom can be rewritten as in Equation (2.54).

$$\theta_i(t) = \left[|x_i(t) - x_{best}(t)|^2 - b_{i,best}^2\right], \tag{2.54}$$

where $x_{best}(t)$ is the optimal atom's location at the *t*th iteration, and $b_{i,best}$ is the length of the fixed bond between the optimal atom and the *i*th one. Therefore, the constraint force is given in Equation (2.55).

$$G_i^d(t) = -\lambda(t)\nabla\theta_i^d(t) = -2\lambda(t)(x_i^d(t) - x_{best}^d(t)), \tag{2.55}$$

where $\lambda(t)$ represents the Lagrangian multiplier and is defined as follows:

$$\lambda(t) = \beta e^{\frac{20t}{T}}, \tag{2.56}$$

where β is the multiplier weight. After 2λ is substituted with λ and β in Equation (2.57), the constraint force is represented as Equation (2.58):

$$G_i^d(t) = \lambda(t)(x_{best}^d(t) - x_i^d(t)). \tag{2.58}$$

Correspondingly, the acceleration of the *i*th atom at *t*th time is shown in Equations (2.59) and (2.60).

$$a_i^d(t) = \frac{F_i^d(t)}{m_i^d(t)} + \frac{G_i^d(t)}{m_i^d(t)}, \tag{2.59}$$

$$a_i^d(t) = -\alpha\left(1-\frac{t-1}{T}\right)^3 e^{-\frac{20t}{T}} \sum_{j\epsilon Kbest} \frac{rand_j\left[2\times(h_{ij})(t)^{13}-\left(h_{ij}(t)\right)^7\right]}{m_i(t)} \frac{\left(x_i^d(t)-x_j^d(t)\right)}{\left\|x_i(t),x_j(t)\right\|_2} +$$

$$\beta e^{\frac{20t}{T}} \frac{x_{best}^d(t)-x_i^d(t)}{m_i(t)}, \qquad (2.60)$$

where $m_i(t)$ is the mass of the *i*th atom at the *t*th iteration and supposed to be measured by its optima value. When the function fitness has a good value, the atom has great mass, thereby reducing its acceleration. The mass of the *i*th atom can be calculated as follows:

$$\mathrm{M}_i(t) = e^{\frac{Fit_i(t)-Fit_{best}(t)}{Fit_{worst}(t)-Fit_{best}(t)}}, \qquad (2.61)$$

$$m_i(t) = \frac{M_i(t)}{\sum_{j=1}^{N} M_j(t)}, \qquad (2.62)$$

where $Fit_{best}^{(t)}$ and $Fit_{worst}^{(t)}$ are the atoms with high and low values of the fitness functions at the *tth* iteration, respectively. $Fit_i(t)$ is the value of the function fitness for the *i*th atom at the *t*th iteration. The following equation represents the $Fit_{best}^{(t)}$ and $Fit_{worst}^{(t)}$:

$$Fit_{\ best}\ (\mathrm{t}) = \min_{i\in\{1,2,..,N\}} Fit_i(t), \qquad (2.63)$$

$$Fit_{\ worst}\ (t) = \max_{i\in\{1,2,..,N\}} Fit_i(t). \qquad (2.64)$$

At the (*t*+1)*t*h iteration, the position and velocity of the *ith* atom can be expressed for simplification:

$$v_i^d(t+1) = rand_i^d\ v_i^d(t) + a_i^d(t), \qquad (2.65)$$

$$x_i^d(t+1) = x_i^d\ v_i^d(t) + v_i^d(t+1). \qquad (2.66)$$

At the initial stage of the iterations, every atom in the population needs to interact with as numerous atoms with the *Kbest* neighbours as possible to enhance the exploration. In the last stage of the iterations, a few atoms need to interact with atoms that have better fitness values as its K neighbours for reinforcing the exploitation.

Whether the interaction force is attraction or repulsion between the atom and its neighbour, it will rely on the ratio of the distance from r_{ij} to σ, which is the length that defines the distance from each atom to the mid location of its K neighbours. Correspondingly, K is a time function, which gradually reduces with iteration lapse. K is formulated as follows:

$$K\ (\mathrm{t})\ =\ \mathrm{N} - (\mathrm{N} - 2) \times \sqrt{\frac{t}{T}}. \tag{2.67}$$

Figure (2) represents the atom population forces, in which *KBest* represents the first five atoms with the optimal objective values. The figure shows that A_1, A_2, A_3 and A_4 form the *KBest*. Variables A_1, A_2, A_3 and A_4 attract or repel one another. By contrast, A_5, A_6 and A_7 attract or repel every atom in the *KBest*. Every atom in the population has a constraint force from the optimal atom A_1, except for A_1 (*xbest*).

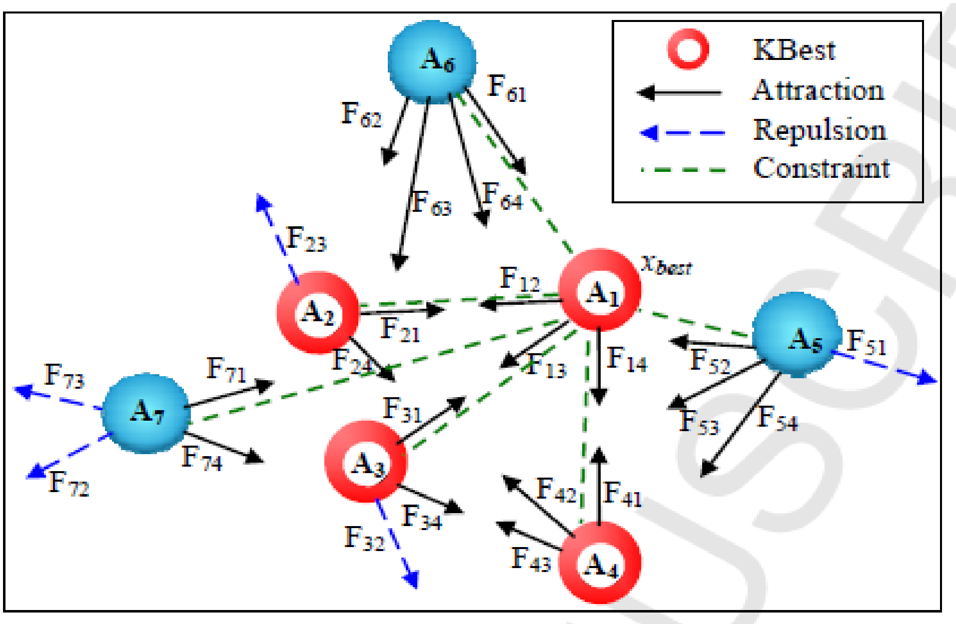

Figure 2: Forces of an Atom System with *KBest* for K = 5.

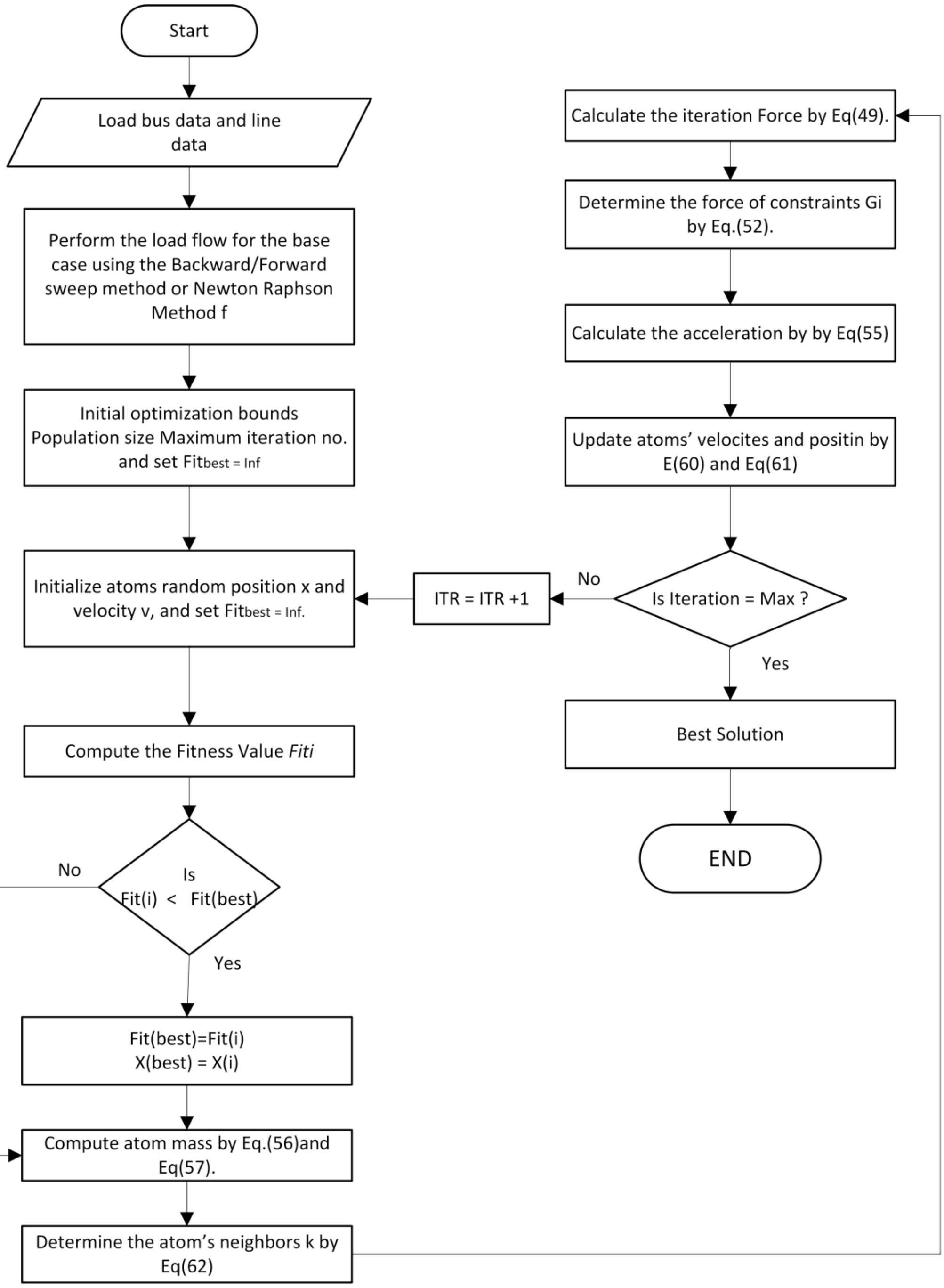

Figure 3: Flowchart of the ASO Algorithm

2.8 ASO vs. Conventional Techniques

The ASO technique varies from usual optimisation and search approaches in the following ways:

1. ASO executes by coding the parameter set and not the parameters themselves.
2. ASO investigates from a population of atoms and not a solo one.
3. ASO utilises objective function intelligence and not the derivative functions or alternative adjunct information.
4. ASO applies probabilistic transition aspects and not the deterministic ones.

2.9 ASO Algorithm for DG Capacity and Placement Challenge

ASO is a newly scientific meta-heuristic strategy that has been improved for global optimisation issues. This strategy is impacted by the fundamental molecular mobility to arithmetically form the movement pattern of atom and is basically established on the interaction and constraint mechanism. Every atom in ASO is influenced by the interaction strength comprised of an appeal and dissonance from its close surroundings and the constraint strength from the atom, which has the superior fitness computation. The atom movement adapts the second law of Newton. The force of attraction motivates the atoms to investigate the entire inspection domain. The repulsive strength permits the atoms to utilise a promising dense space. This approach is adapted to achieve the multi-objective DG optimal capacity and size in the power systems. Figure (3) illustrates the flowchart for the system where the technique procedure is depicted as follows:

Step 1: Read the data for the power system network inclosing the bus and branch data.

Step 2: Perform the load flow for the base case to determine the bus voltages and total power losses. Calculate the PF.

Step 3: Set the initial data, such as the number of DGs and buses, for the system.

Step 4: Define α and β values for the optimisation.

Step 5: Identify the initial values, such as atom numbers, maximum number of iterations and the stopping criteria, for the optimiser.

Step 5: Call the optimiser, and set the iteration counter = 1, and Fit_{best}=Inf.

Step 6: Specify the upper and lower limits inside the optimiser for the DG size and location.

Step 7: Check the stopping criteria if it hits the limit, and then proceed to the end.

Step 8: Randomly initialise the positions and velocities of atoms.

Step 9: Run the power flow to satisfy the objective functions

Step 10: Check for constraint satisfaction, and add penalty for undesired values.

Step 11: Calculate the fitness value Fit_i if the present one is less than the optimal fitness, then assign the present value to be the optimal fitness. Otherwise, return to Step 7.

Step 12: Compute the mass by using Equations (56) and (57).

Step 13: Define the atom's neighbours by using Equation (62).

Step 14: Calculate the interaction force by using Equation (49).

Step 15: Compute the constraints force by utilising Equation (52).

Step 16: Determine the acceleration by applying Equation (55).

Step 17: Update the velocity and position of every atom by utilising Equations (60) and (61), respectively.

Step 18: If the number of atoms reaches the maximum, or the iteration counter hits the limit or the stopping criteria breaks the bounds, then proceed to the next step. Otherwise, increase the counter by one, and return to Step (8).

Step 20: Display the optimal solution $X_{best.}$

Figure (3) illustrates the flow chart for ASO DG sizing and locating.

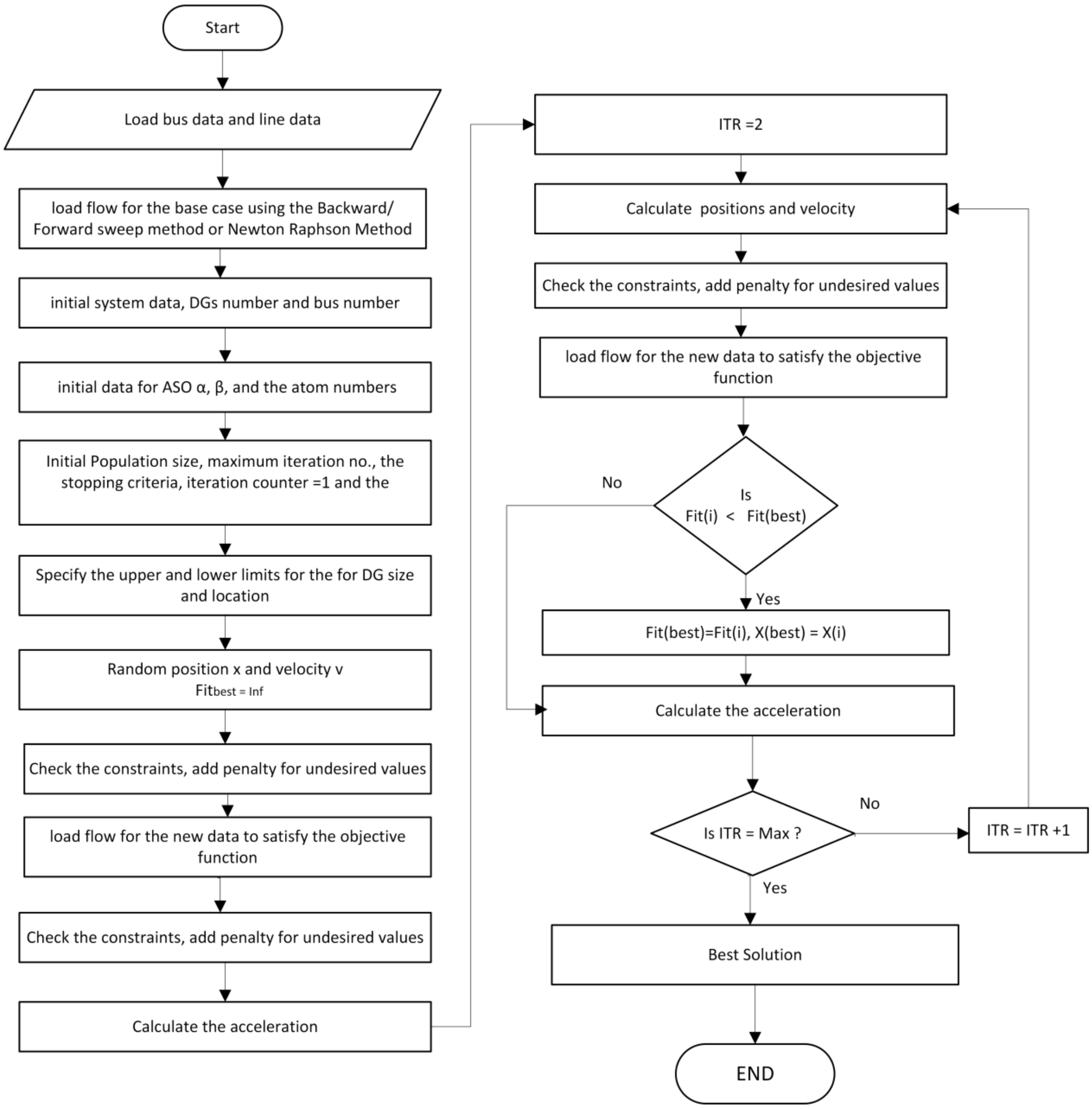

Figure 4: Flowchart for ASO DG Sizing and Locating

2.10 Chapter Summary

This chapter proposed the equations of the power flow, mathematical formulation of the power loss and the equations for calculating the operating cost. Four AI methods, namely, GA, PSO, GA-PSO and ASO, were implemented to resolve the problems that were presented and discussed in addition to their working procedures.

Chapter 3: Results and Discussion

This chapter presents the results of the optimal allocation and capacity of DG in power networks (RDS and transmission network) by using the GA-PSO and ASO techniques. The proposed technique was implemented and programmed in MATLAB R 2017b in a computer with Intel Core i7, 2.59 GHz and 8 GB of RAM. The algorithm was evaluated to verify the effectiveness, robustness and efficiency of the proposed ASO technique.

Table 1: Parameter Values for GA-PSO and ASO

Parameters	GA-PSO	ASO
Population size	50	50
Maximum iteration number	200	200
Maximum error	$1x10^{-9}$	$1x10^{-9}$

The techniques were tested to be evaluated on the IEEE test systems, namely are 14 and 33 bus test systems. The ASO is utilised to specify the placement and capacity of DGs for comparative aims using the GA-PSO method. In this thesis, 1, 2 and 3 DGs, which operate in PF ≥ 0.8, are considered. Table (1) shows the parameter settings for both methods. Both techniques were adjusted to have the same parameter values for comparing the performance and effectiveness of the proposed approach. Table (2) illustrates the parameters that are used to calculate the operating cost for the DGs. Below is a detailed discussion of the two different IEEE test systems that are utilised to evaluate the proposed strategy.

- IEEE 14 Meshed bus system

- IEEE 33 RDS

Table 2: Operation Cost Variables for the 14 and 33 Bus Systems

variables	33 bus system	14 bus system
Weighting coefficient α	1.01	1.03
Investment Costs /$kW^{-1}	1400	1400
Maintenance Costs /$ (kW h)$^{-1}$	0.03	0.03
On-Grid price /$(kW. h)$^{-1}$	0.15	0.15
Efficiency of DG (η)	13.44%.	13.44%.
Discount rate (d)	0.12	0.12
maximum houre($T_{MH)}$)(h)	3000	3000
Equivalent generation huor(T_{eqh})	3000	3000
Number of DGs (M)	1DG, 2DGs, 3DGs	1DG, 2DGs, 3DGs
Life time of DG($LTDG$)	5	5

The DG type that is used in this study is a synchronous generator generation unit. This this type of renewable energy can supply active and reactive powers to the system with a rated power of 2 MW in the 33 bus system and 80 MW in the 14 bus system. In this approach, the placement and sizing of DGs in the distribution system are considered a problem dimension and represented as variable parameters to formulate the optimisation problem. The DG location is defined as the integer variable of the problem. The placement and capacity of the DGs are expressed in the ASO as a vector Table (3):

Table 3: Placement and Capacity Variables Using 3, 2 and 1 DGs

DG	Bus Number	Real capacity (kw)	Reactive capacity

no.							(Kvar)		
3DGs	B1	B2	B3	P1	P2	P3	Q1	Q2	Q3
2DGs	B1	B2		P1	P2		Q1	Q2	
1DG	B1			P1			Q1		

Where B1, B2 and B3 are the DG bus locations; and P1, P2 and P3 and Q1, Q2 and Q3 are the active and reactive capacities of the DGs, respectively.

The constraint values for the system are presented as follows:

- The upper and lower limits for the DG placements are bus numbers 2 and 33 for the 33 bus system and 2 and 14 for the 14 bus system.
- The upper and lower limits for the capacity are 0% and 80% of the bus load, respectively. The total capacity of the DGs should be ≤30% of the total system loads in 33 RDS. By contrast, the capacity limits are from 0 M to 2 M in the 14 bus system (the rated power of the DGs).
- The allowable values of voltage magnitudes on the buses are 5% of the rated voltage between 0.95 and 1.05.
- The accepted values for the PF should be >0.8.

3.1 IEEE 14 Bus System

The IEEE 14-bus test system shows the grid topology with a 12.66 kV as base voltage of the system with 1 main supply station, 14 buses, 20 feeders, 2 generators, 3 synchronous compensators, 10 load points and double two-winding and three-winding transformers Figure (5). The feeders and transformers were designed using pi-equivalent circuits. Bus number 1 is considered a reference or slack bus. The synchronous compensators and generators were designed by using the active and reactive power steady states and the restrictions of the reactive power generation. The network has 362.6 MW as a total active power demand load and 113.96 MVAR as a total reactive power as a demand load; moreover, the system has a 392.05 MW as a total real power generation and 205.54 MVAR as a total reactive power generation (Candelo et al., 2013). The base apparent power for the system is 100 MVA. The total real and reactive power losses for the system are 13.393 MW and 54.54 MVAR, respectively. The proposed technique is implemented by utilising MATLAB software to compute the optimal location and capacity of the DGs. Tables (10) and (11) show the bus and line data for the system, respectively. Before the DGs are added to the power system, a power load flow procedure based on the NR method is applied to obtain the system conditions. Table (12) presents the power flow results, which designate the magnitudes of the node voltage for the buses of the system. The DG optimal placement and capacity issue is implemented for one operating point where the loads are assumed to be fixed in all cases. The demand active (Pd) and reactive power (Qd) are specified in MW and MVAR, respectively. By contrast, the line resistance (R) and feeders' reactance (X) are expressed in per unit (pu). With regard to the bus types, bus numbers 1, 2 and correspond to a PQ bus, a PV bus and a slack bus, respectively.

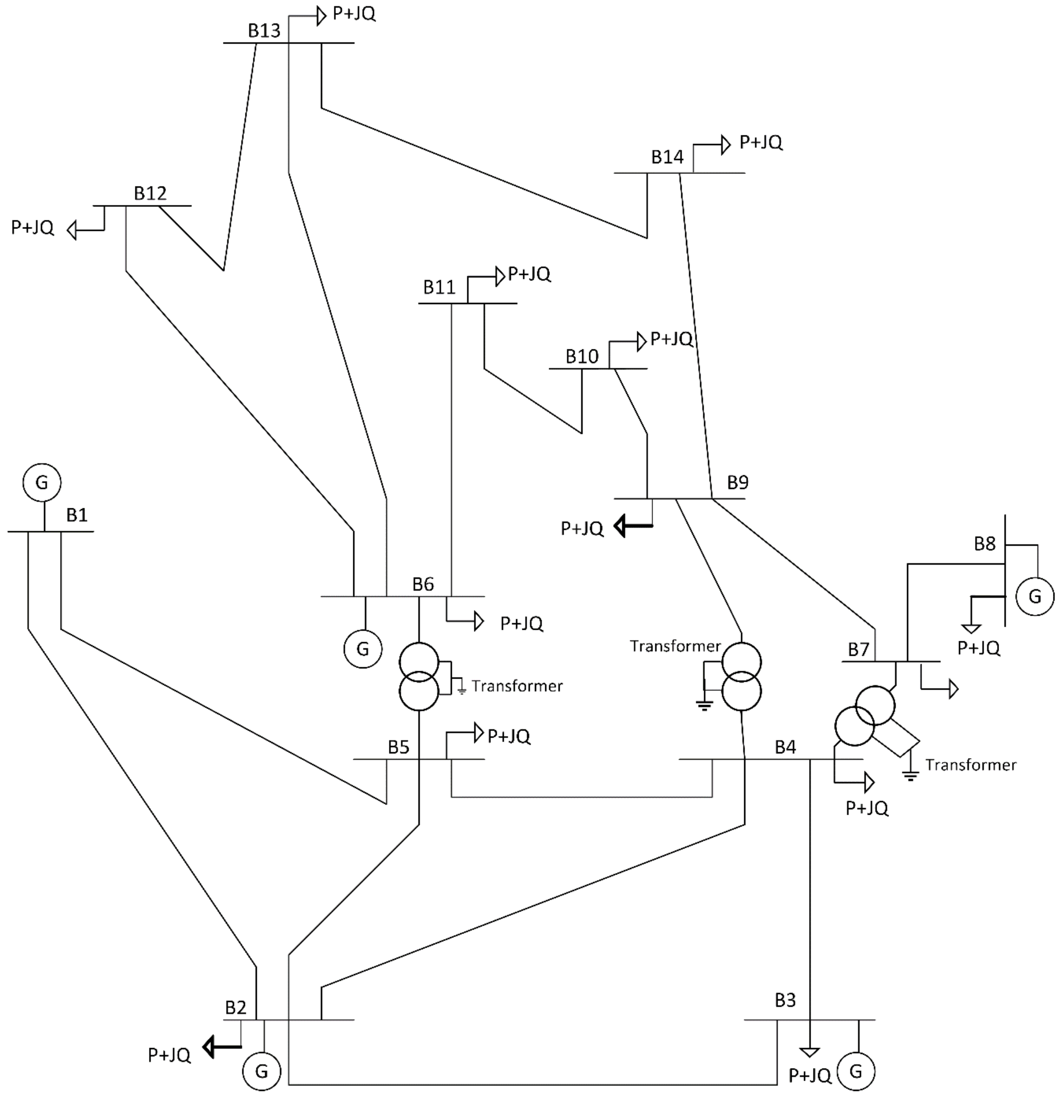

Figure 5: Single line diagram for the IEEE 14 Bus system

In Figure (5), G and B represent the generators and bus numbers, respectively.

The application of a power flow code using NR method is an advance stage to obtain the IEEE 14 bus system power loss and the voltage magnitudes on the buses. The parameter values from (Almagboul et al., 2019) that are used in the ASO technique are presented as follows:

- Population size = 50

- Depth weight (α) = 50
- Multiplier weight (β) =0.2
- Maximum number of iteration= 200

Various cases for the IEEE 14 bus power system are investigated on the basis of the number of DGs (i.e. 1, 2 and 3 DGs). The capacity range of the DG is from 0 M to 80 M.

Case 1: This system is demonstrated by installing a single DG. ASO is applied to specify the optimum capacity and position of the DG in the system.

Case 2: In this case, the system is presented by applying two DGs by using ASO to identify the optimal size and location of the DGs on the buses.

Case 3: The system in this case investigates the utilisation of ASO to specify the optimum placement and size of three DGs in the 14-bus RDS.

The maximum operating cost is considered on the basis of the summation of the maximum installed capacity of each DG in the system to calculate the normalised operating cost. The maximum operating costs for 1, 2 and 3 DGs are 3.4698×10^6, 3.6591×10^6 and 1.0503×10^7, respectively.

Before placing the DG, the voltage magnitudes were poor because the voltages in most buses were adjacent to the lower boundary of the identified limits. Nevertheless, the magnitude was improved after the DGs were applied to its optimum location and capacity Figure (6). The values of the voltage nodes at buses 2 to 5 were significantly enhanced, similar to buses 9, 10 and 14. Applying 3 DGs in the network system resulted in superior enhancement in the voltage profile compared with 1 and 2 DGs.

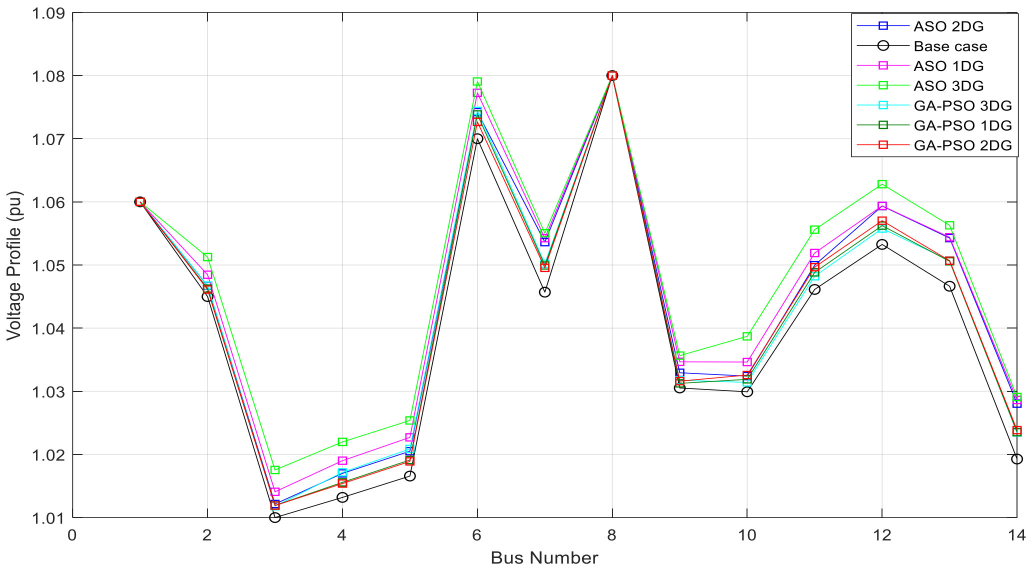

Figure 6: Voltage Profile for the 14 Bus System

Figure (6) exhibits that voltage magnitudes in all cases that adapt GA-PSO are weaker compared with those obtained from the ASO technique. Installing 3 DGs in the power system by using GA-PSO exhibits better results than installing 1 DG or 2 DGs in buses from 2 to 5. By contrast, attaching 2 DGs improves the voltage profile in buses 9, 10, 11 and 14. The results verified that the proposed method presents better results in terms of enhancing the voltage profile compared with GA-PSO.

Power losses in the lines is the second objective function where the power loss base obtained from applying the NR method is 13.593 MW. Figure (7) illustrates the power loss after ASO and GA-PSO are applied on the 14-bus system and 1, 2 and 3DGs are individually injected. The figure demonstrates that the use of ASO with 1 DG is an effective case. By contrast, the worst case is the implementation of GA-PSO with 3 DGs.

Table (4) presents power loss and loss saving in addition to the percentage of power loss reduction that resulted from the implementation of ASO and GA-PSO algorithms in the 14-bus system.

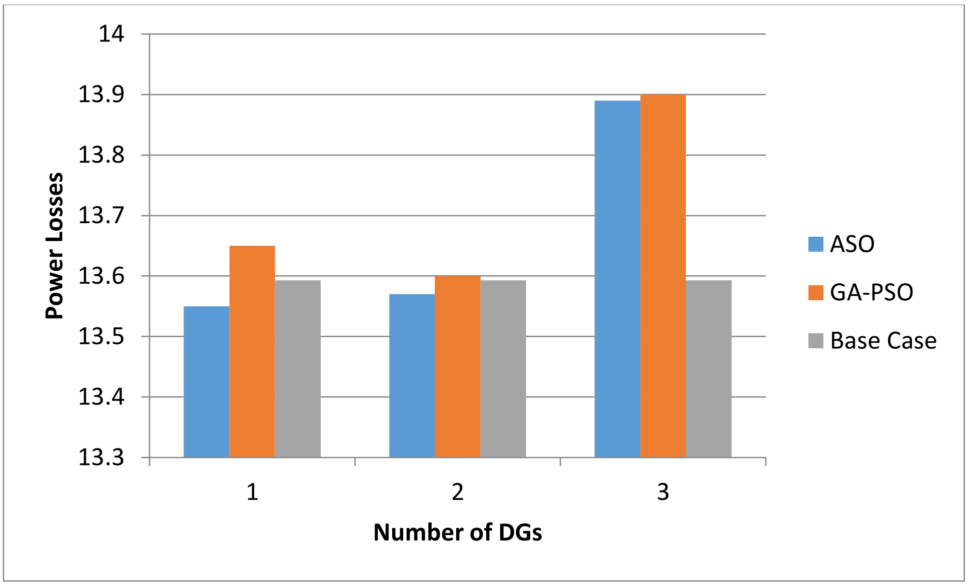

Figure 7: Power Loss in the 14 Bus System

Table 4: Power Loss in the 14 Bus System

Method	ASO			GA-PSO		
power	1 DG	2 DGs	3 DGs	1DG	2DGs	3DGs
P loss Base (MW)	13.593	13.593	13.593	13.593	13.593	13.593

Power loss DG (MW)	13.55	13.57	13.89	13.65	13.6	13.9
Loss Saving (MW)	0.043	0.023	-0.297	-0.143	-0.007	-0.05
Power loss reduction %	0.316	0.169	-2.18	-0.004	-0.051	-2.259
CPU time (s)	62.39	61.13	61.13	123.573	122.484	121.437

Figure (4) shows the power losses in all the cases (i.e. 1, 2 and 3 DGs). The installation of 1 DG to the 14-bus system is sufficient. The power losses are the lowest with a value of 13.55 MW and a reduction percentage of 0.316% compared with other cases. By contrast, the results obtained from the GA-PSO show that the optimisation failed to reduce the power losses Figure (7) and Table (4).

The ASO results clearly verify the effectiveness and influence of this novel algorithm compared with the outcome attained from the GA-PSO method. The optimum location and size from the ASO provides 0.043 MW compared with -0.143 MW by the GA-PSO technique.

Table 5: DGs Capacity and Location for the 14 Bus System

Method	DG location			DG capacity					
	1DG	2DGs	3DGs	1DG		2DGs		3DGs	
				P(MW)	Q(Mvar)	P(Mw)	Q(Mvar)	P(MW)	Q(Mvar)
ASO	8	2 6	8 10	0	2	4 4	4 6	0 1	1 4

			7					0	0
GA- PSO	11	10 5	7 13 12	20	20.994	0.5 0.5	9.414 10.87	0.019 3.9 0.5	0.123 0.5 1.9

Table (5) illustrates the optimal placement of the DGs in the 14-bus system with their corresponding active and reactive power sizes. Tables (4) and (5) show the acquired results from the proposed ASO technique in bus 8 with 1 DG case. Such case provided superior power loss reduction and proper placement for DG implementation with sizes of 0 MW and 2 MVAR. This finding indicates that only a reactive power is injected to the system. On the contrary, the GA-PSO method proposed that bus 11 is the optimal placement with 20 MW and 20.994 MVAR. The results obtained from Figure (6) shows that the ASO with 3 DGs on buses 4, 6 and 12 presented the highest voltage profile enhancement compared with the other cases in ASO and GA-PSO.

The CPU time in Table (4) indicates that the proposed ASO take less simulation time to run the optimisation than GA-PSO where the average time needed for ASO is 61.55 s. By contrast, the average required time for GA-PSO to execute the simulation is 122.5 s.

Table 6: Operating Cost for the 14 Bus System

Cost parameters	ASO			GA-PSO		
	1DG	2DGs	3DGs	1DG	2DGs	3DGs
Generation cost (k$)	0.040	53.65	120.59	48.37	54.457	404.59
Investment cost (k$)	0.30	407.5	918.62	323.232	425.394	3116.30
Maintenance cost (K$)	0.0697	92.12	207.06	80.1	93.071	694.696
Operation cost (k$)	0.336	445.97	1005	263.96	572.85	1406.41

This study considers operating cost as a third objective function. The operating cost of the DG units that comprise generation, investment and maintenance costs plays an important role in specifying the DG capacity. The high degree of penetrating the DGs in the power system will increase the investment and maintenance costs. Table (6) demonstrates that the operating cost for the GA-PSO is more expensive than that of the ASO. The optimiser injected 1 DG with only a reactive power, which costs less than the system with active and reactive power together. This notion indicates a non-optimal capacity of the utilised DGs in the power system when the GA-PSO algorithm is used.

3.2 IEEE 33 RDS

Figure (8) depicts the grid topology of the IEEE 33-bus test system, that is, a RDS with a 12.66 kV as base voltage of the system with 1 substation, 33 buses and 32 feeders. The network has 3.715 MW as a total active power demand load and 2.3 MVAR as a total reactive power as a demand load (Dharageshwari and Nayanatara, 2015). The base apparent power for the system is 100 MVA. Bus number 1 is considered a slack or reference bus, and the other buses are load buses. The total real and reactive power losses for the system are 187 kW and 110 KVAR, respectively. The proposed technique is implemented by utilising MATLAB software to compute the optimal location and capacity of the DGs. Tables (13) and (14) show the bus and line data for the system, respectively. Before the DGs are added to the power system, a power load flow procedure based on the backward forward method is applied to obtain the system conditions. The data for the buses and lines are stored in a MATLAB file. Table (15) shows the results of the power flow that designate the magnitudes of the node voltage and the PF for the system buses. The DG optimal placement and capacity issue is implemented here for one operating point where the loads are assumed to be fixed in all cases. The demand active power (Pd) and the reactive power (Qd) are specified in KW and kVAR, respectively. By contrast, the line resistance (R) and feeders' reactance (X) are in pu. The table demonstrates that the PF for bus 30 is 0.316228. Thus, the reactive power load on the bus has been changed to 100 kVAR instead of 600 kVAR to enhance its PF. Table (16) shows the voltage magnitudes and power factor on the buses after the reactive power on bus has been modified to 30. With regard to bus types, bus numbers 1, 2 and 3 correspond to a PQ bus, PV bus and slack bus, respectively.

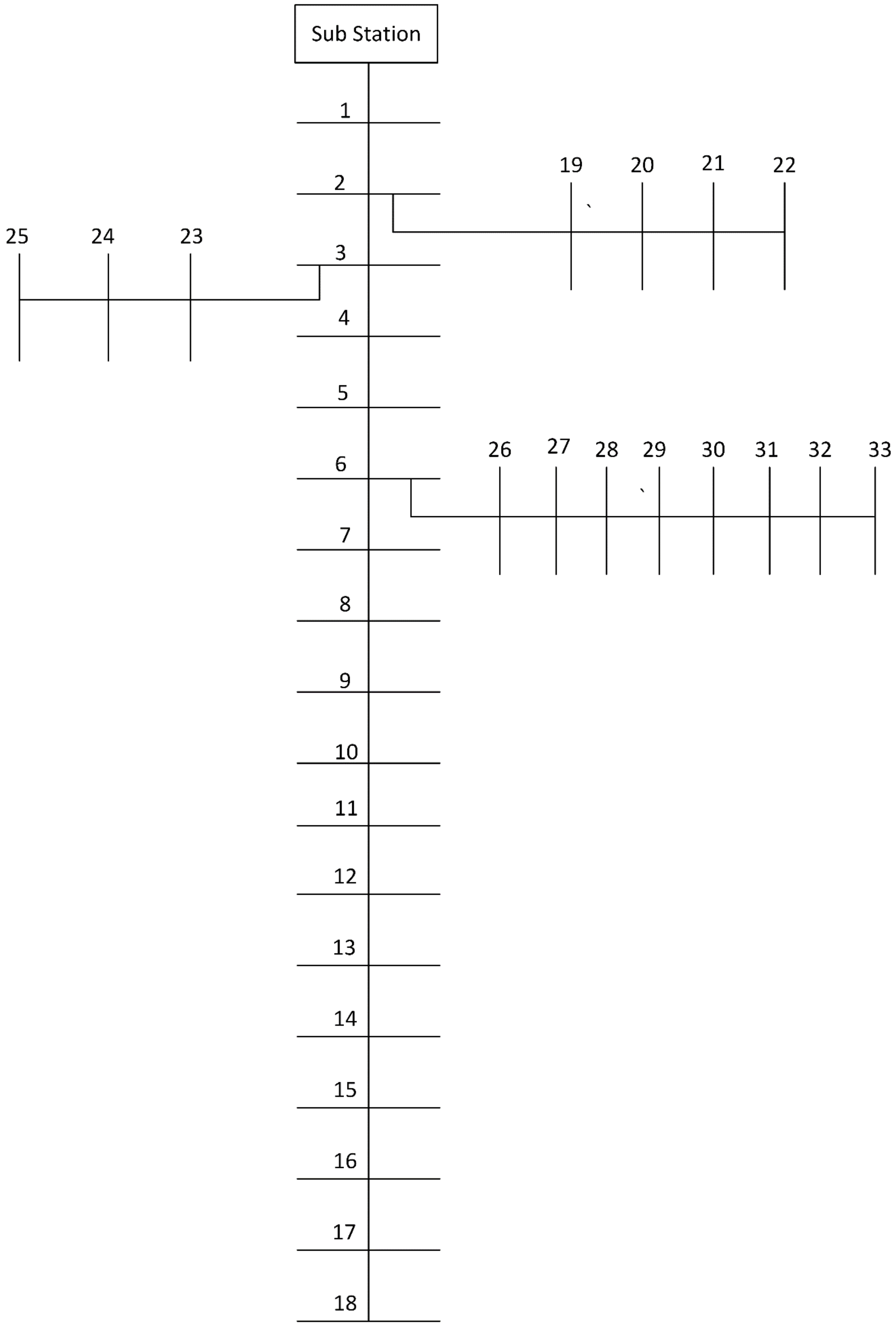

Figure 8: Single Line Diagram for the IEEE 33 Bus System

Before the DGs are implemented, a power flow programme based on the backward–forward sweep method is applied to determine the IEEE 33 bus system power loss, as well as the voltage on the buses.

The parameter values from (Almagboul et al., 2019) that are used in the ASO technique are presented as follows:

- Population size = 50
- Depth weight (α) = 50
- Multiplier weight (β) =0.2
- Maximum number of iteration= 200

Several cases are investigated for the power system of the IEEE 33 bus on the basis of the number of DGs (1, 2 and 3).

Case 1: This system is represented by installing a single DG. ASO is applied to specify the optimum capacity and position of the DG in the system.

Case 2: In this case, the system is demonstrated by applying two DGs by using ASO to identify the optimal size and location of the DGs on the buses.

Case 3: The system in this case investigates the utilisation of ASO to specify the optimum placement and size of three DGs in the 33 bus RDS.

The maximum operating cost is considered on the basis of the summation of the maximum installed capacity of each DG in the system to calculate the normalised operating cost. The maximum operating costs are 1.4573×10^5, 2.9277×10^5 and 4.411×10^5 for 1, 2 and 3 DGs, respectively.

The voltage profile at the buses is plotted in Figure (6), where the voltage magnitudes are compared with the system before and after installing 1 DG once, 2 DGs in another time and 3 DGs in the ASO and GA-PSO techniques. ASO is applied to enhance the voltage magnitudes of the buses influenced by the number of DGs connected to the system. The voltage profile with 1 and 2 DGs has similar values compared with the voltage values with 3 DGs. The use of 1 and 2 DGs rather than 3 DG provide better results, and the voltage values are closer to the unity than when 3 DGs are utilised.

Before locating the DG, the voltage magnitudes were poor because the voltages in most buses were adjacent to the lower boundary of the identified limits. Nevertheless, the magnitude was significantly promoted after the DG capacity was applied to its optimum location Figure (6). The voltage node values at buses 6 to 18 were significantly increased, similar to buses 24 to 32.

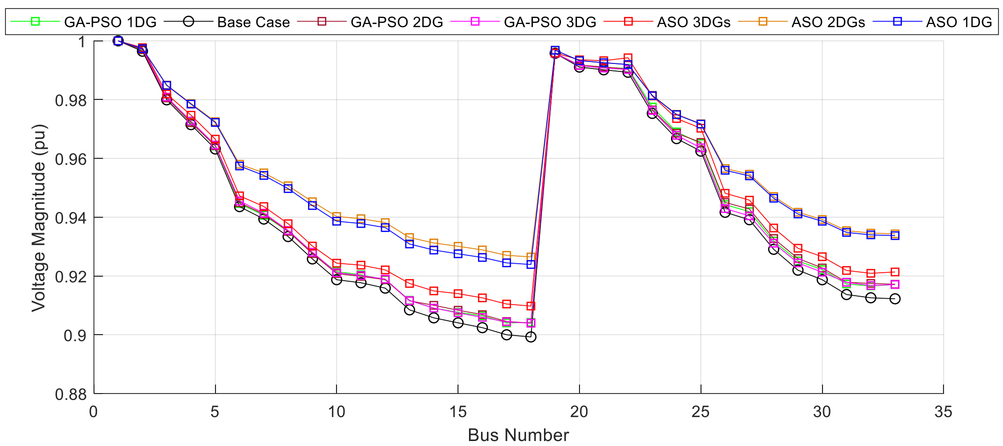

Figure 9: Voltage Profile for the 33 Bus System

Figure (9) demonstrates that the values of the voltages in all cases by utilising GA-PSO are poor compared with those from the ASO. Nevertheless, penetrating 2 DGs in the distribution system by using GA-PSO presents better results than installing 1 DG or 3 DGs. The results verified that the proposed method presents better results in terms of enhancing the voltage profile compared with GA-PSO.

The second objective function is the power loss in the feeders where the power loss base obtained from applying the backward–forward sweep method is 186.657 kW.

Figures (10) and (11) show the power losses in the system after ASO and GA-PSO are applied on the 33-bus system by independently injecting 1, 2 and 3 DGs. The figure demonstrates that the most effective case is the use of ASO with 2 DGs, whilst the worst one is the implementation of GA-PSO with 3 DGs.

Table (7) reflects the results obtained from Figures (10) and (11). The power loss resulted from the implementation of ASO and GA-PSO algorithms to determine the power loss and loss saving, in addition to the percentage of power loss reduction in the system.

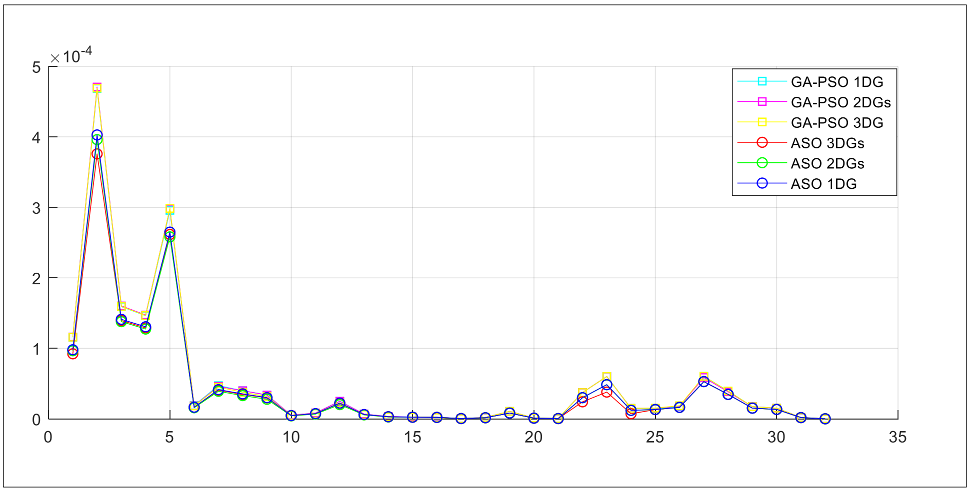

Figure 10: Power Loss in the 33 Bus System

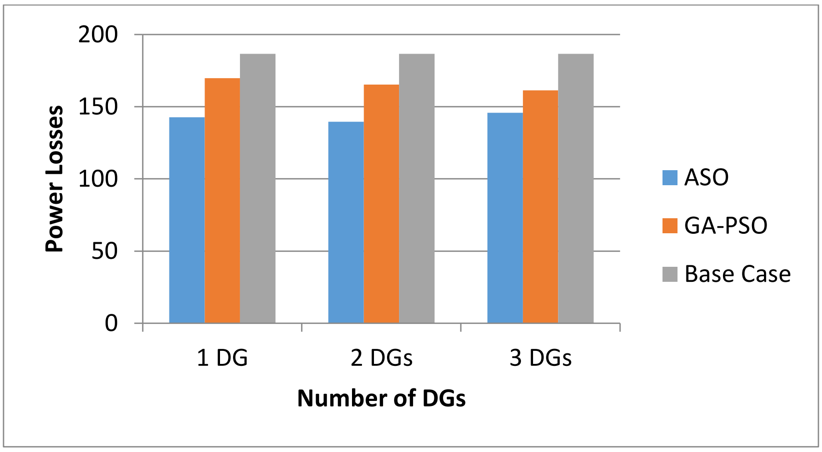

Figure 11: Flowchart of Power Loss in the 33 Bus System

Table (7) shows that the power loss for the base case of the system before installing any DG is 186.657. The table illustrates that the optimal loss saving and reduction percentage are achieved when the ASO is utilised with 2 DGs. The 1 DG showed good results in improving the voltage profile minimising the power loss.

Table 7: Power Loss in the 33 Bus System

Method	ASO			GA-PSO		
power	1 DG	2 DGs	3 DGs	1DG	2DGs	3DGs
P loss Base (KW)	186.657	186.657	186.657	186.657	186.657	186.657
Power loss (KW)	142.58	139.58	145.8997	169.668	165.348	161.28
Loss Saving (KW)	44.077	47.077	40.7573	16.989	21.309	25.377
Power loss reduction %	23.77	25.38	21.83	9.102	11.461	13.638
CPU time (s)	58.610511	61.333	75.1611	65.097063	84.587807	99.448808

Table (8) illustrates the size and placement for the DGs in the power system as a result of the application of ASO and GA-PSO for comparison purposes. Tables (7) and (8) demonstrate that the DG placement presents a loss reduction of 25.38% because of its location at the end of the system when the ASO is utilised for 2 DGs. By contrast, loss reduction saving is 13.638% when GA-PSO is used for 3 DGs. Table (8) shows the locations for the DGs. This result shows that this bus is a non-optimal location with a non-optimal size. When the GA-PSO is applied with 3 DGs, better results are achieved compared with 1 DG and 2 DGs. Nevertheless, the use of ASO presents superior results. The CPU time consumption for running the simulation code by MATLAB software manifests that ASO with 1 DG consumes less time than any other cases. Similarly, GA-PSO with 1 DG takes a short time to execute the code.

Table 8 : Capacity and Location of DGs in the 33 Bus System

Method	DG location			DG capacity					
	1DG	2DGs	3DGs	1DG		2DGs		3DGs	
				P(Kw)	Q(Kvar)	P(Kw)	Q(Kvar)	P(Kw)	Q(Kvar)
ASO	17	15 13	9 26 15	8	4	1 1	44 23	1 1 1	12 13 5
GA-PSO	27	28 17	5 17 18	20	32	1.84 6.05	20.32 30.1	5 5 5	7.7 12.5 20.05

This study considers the operating cost as a third objective function. The DG unit operating cost, which includes the generation, investment and maintenance costs, plays an important role in selecting the DG capacity. The high degree of dispersion for the DGs will increase the investment and maintenance costs. Table (9) illustrates that the operating cost for the GA-PSO is more expensive than that of ASO because of the non-optimal capacity of the utilised DGs in the power system.

Table 9: Operation Cost for the ASO 33 Bus System

Cost parameters	ASO	GA-PSO

	1DG	2DGs	3DGs	1DG	2DGs	3DGs
Generation cost (k$)	52.416	53.65	120.59	1048.55	413.567	786.24
Investment cost (k$)	396.141	407.5	918.62	2924.587	3149.098	6000.375
Maintenance cost (K$)	90	92.12	207.06	1800.401	710.1	1350
Operation cost (k$)	433.725	445.97	1005	2172.736	3445.639	6564.13

3.3 Chapter Summary

This chapter presents the results obtained from applying ASO on 14-bus transmission system and 33-bus RDS. The results are compared with those of the GA-PSO algorithm. The voltage profile enhancement, power loss reduction and operational expenses on the 33-bus RDS are carried out effectively with rigid robustness.

Chapter 4: Conclusion

DGs are essential components in power networks because of their effective influence in mitigating power losses, enhancing voltage profile and reducing the operating cost of the power systems. These goals can be obtained depending on the DGs location in the power system with appropriate capacity.

This thesis proposes a novel meta-heuristic ASO approach that can be applied to the nonlinear and non-convex power system problem. Such approach can obtain the DG optimal placement and optimal capacity with multi-objective advantages, namely, power loss reduction, VPI and operation expense decrement. The results of this technique have been compared with those obtained from GA-PSO algorithm. In this thesis, two load flow analyses, namely, Newton–Raphson method and backward–forward sweep method have been applied on a transmission network and a RDS, respectively. Two different IEEE test systems, namely, 14-bus system and 33-bus RDS, have been tested to evaluate the effectiveness and influence of the proposed algorithm. Three scenarios are also included in the research, and 1, 2 and 3 DGs have been installed. DGs inject active and reactive power to the system. The results verified the effectiveness of ASO compared with the results obtained from GA-PSO where the optimal placement and capacity satisfy a high power saving of 14.75 MW for ASO compared with the 1.8 MW for GA-PSO in the 14-bus system. By contrast, the power saving for ASO is 47.077 compared with GA-PSO in the 33-bus RDS. The cost obtained from ASO is more profitable than those gained from GA-PSO.

The effectiveness and influence of ASO on the 33-bus RDS are better than those of ASO on the transmission system. Such system has generators, synchronous compensators and two-winding and three-winding transformers. Specifically, the transmission system has PV and PQ buses apart from the slack bus. Meanwhile, 33-bus RDS only has PQ buses and the slack bus. The ratio X/R is low in the radial systems compared with that in the transmission ones, thereby increasing the power losses in the radial systems.

ASO is a meta-heuristic optimisation technique with expeditious convergence rate, few adjustable parameters, simple operation and rigid robustness.

4.1 Future Work

This thesis is operated on a single operating point where the load is assumed to be fixed. The application of the optimisation on variable loads is a target for future work. Other objective functions, such as voltage stability index, will be added to the system. Another idea is to determine whether the DG placement and sizing issue in transmission networks are compatible with dispatch reactive power problem.

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Idris Abdelrahman, Shareef Hussain, Md. Mainul ISLAM, Siddiqul AKBAR and Akhatib Ashwaq. 2019. “Coordinated Allocation of Dispersed Reactive Power Resources for Voltage Regulation and Loss Minimization”. *International Journal of Engineering & Technology* 8(1.7):153-161.

Appendix

Table 10: 14 Bus System Bus Data

Bus No	Bus Type	Pd	Qd
1	3	0	0
2	2	21.7	12.7
3	2	94.2	19
4	1	47.8	-3.9
5	1	7.6	1.6
6	2	11.2	7.5
7	1	0	0
8	2	0	0
9	1	29.5	16.6
10	1	9	5.8
11	1	3.5	1.8
12	1	6.1	1.6
13	1	13.5	5.8
14	1	14.9	5

Table 11: 14 Bus System Line Data

From Bus	To Bus	R	X
1	2	0.01938	0.05917
1	5	0.05403	0.22304
2	3	0.04699	0.19797
2	4	0.05811	0.17632
2	5	0.05695	0.17388
3	4	0.06701	0.17103
4	5	0.01335	0.04211
4	7	0	0.20912
4	9	0	0.55618
5	6	0	0.25202
6	11	0.09498	0.1989
6	12	0.12291	0.25581
6	13	0.06615	0.13027
7	8	0	0.17615
7	9	0	0.11001
9	10	0.03181	0.0845
9	14	0.12711	0.27038
10	11	0.08205	0.19207
12	13	0.22092	0.19988
13	14	0.17093	0.34802

Table 12: 14 Bus System Voltage Magnitudes

Bus No	Vm (pu)
1	1.06
2	1.045
3	1.01
4	1.019
5	1.02
6	1.07
7	1.062
8	1.09
9	1.056
10	1.051
11	1.057
12	1.055
13	1.05
14	1.036

Table 13: 33 Bus System Bus Data

Bus No	Bus Type	Pd	Qd
1	3	0	0
2	1	100	60
3	1	90	40
4	1	120	80
5	1	60	30
6	1	60	20
7	1	200	100
8	1	200	100
9	1	60	20
10	1	60	20
11	1	45	30
12	1	60	35
13	1	60	35
14	1	120	80
15	1	60	10
16	1	60	20
17	1	60	20
18	1	90	40
19	1	90	40
20	1	90	40
21	1	90	40
22	1	90	40
23	1	90	50
24	1	420	200
25	1	420	200
26	1	60	25
27	1	60	25
28	1	60	20
29	1	120	70
30	1	200	600
31	1	150	70
32	1	210	100
33	1	60	40

Table 14: 33 Bus System Line Data

From Bus	To Bus	R	X
1	2	0.0922	0.047
2	3	0.493	0.2511
3	4	0.366	0.1864
4	5	0.3811	0.1941
5	6	0.819	0.707
6	7	0.1872	0.6188
7	8	0.7114	0.2351
8	9	1.03	0.74
9	10	1.044	0.74
10	11	0.1966	0.065
11	12	0.3744	0.1238
12	13	1.468	1.155
13	14	0.5416	0.7129
14	15	0.591	0.526
15	16	0.7463	0.545
16	17	1.289	1.721
17	18	0.732	0.574
2	19	0.164	0.1565
19	20	1.5042	1.3554
20	21	0.4095	0.4784
21	22	0.7089	0.9373
3	23	0.4512	0.3083
23	24	0.898	0.7091
24	25	0.896	0.7011
6	26	0.203	0.1034
26	27	0.2842	0.1447
27	28	1.059	0.9337
28	29	0.8042	0.7006
29	30	0.5075	0.2585
30	31	0.9744	0.963
31	32	0.3105	0.3619
32	33	0.341	0.5302
21	8	2	2
9	15	2	2
12	22	2	2
18	33	0.5	0.5
25	29	0.5	0.5

Table 15: 33 Bus System Voltage Magnitudes and Power Factors before System Modification

Bus No	Vm (pu)	PF
1	1	1
2	0.996367	0.857493
3	0.97928	0.913812
4	0.970075	0.83205
5	0.960998	0.894427
6	0.938432	0.948683
7	0.934157	0.894427
8	0.928215	0.894427
9	0.920576	0.948683
10	0.913501	0.948683
11	0.912453	0.83205
12	0.910629	0.863779
13	0.903221	0.863779
14	0.900484	0.83205
15	0.89878	0.986394
16	0.897128	0.948683
17	0.894691	0.948683
18	0.893959	0.913812
19	0.995672	0.913812
20	0.990973	0.913812
21	0.990048	0.913812
22	0.989212	0.913812
23	0.975113	0.874157
24	0.967423	0.902861
25	0.964043	0.83205
26	0.93608	0.923077
27	0.932959	0.923077
28	0.919024	0.948683
29	0.909023	0.863779
30	0.904714	0.316228
31	0.899643	0.906183
32	0.898528	0.902861
33	0.898182	0.83205

Table 16: 33 Bus System Voltage Magnitudes and Power Factors after System Modification

Bus No	Vm(pu)	PF
1	1	1
2	0.996367	0.857493
3	0.97928	0.913812
4	0.970075	0.83205
5	0.960998	0.894427
6	0.938432	0.948683
7	0.934157	0.894427
8	0.928215	0.894427
9	0.920576	0.948683
10	0.913501	0.948683
11	0.912453	0.83205
12	0.910629	0.863779
13	0.903221	0.863779
14	0.900484	0.83205
15	0.89878	0.986394
16	0.897128	0.948683
17	0.894691	0.948683
18	0.893959	0.913812
19	0.995672	0.913812
20	0.990973	0.913812
21	0.990048	0.913812
22	0.989212	0.913812
23	0.975113	0.874157
24	0.967423	0.902861
25	0.964043	0.83205
26	0.93608	0.923077
27	0.932959	0.923077
28	0.919024	0.948683
29	0.909023	0.863779
30	0.904714	0.316228
31	0.899643	0.906183
32	0.898528	0.902861
33	0.898182	0.83205